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USC UNIVERSITY OF SOUTHERN CALIFORNIA

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UCLA

Notification

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The study results reported for EV Use Case 8 are based on the assumptions and data discussed in the report and are conducted using MATLAB, PSCAD, and EDD analysis models. No thorough review has been done to assess the accuracy of the data or the analysis models for the purpose of this study and thus, USC doesn't warranty the accuracy or the use of these study results. The MATLAB, EDD, and PSCAD power system analysis models are preparatory models supplied by the respective venders.

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This document describes the progress of the Los Angeles Department of Water and Power (LADWP) in establishing the cyber security of the smart grid. Cyber Security Team's work was carried out by LADWP Information Technology Services (ITS) and by the Jet Propulsion Laboratory (JPL).

To provide context, this document includes descriptions of JPL's recent work, which was funded solely by LADWP (outside LADWP's DoE-funded Smart Grid Regional Demonstration Project, or SGRDP) as well as some of the foundation work performed as part of the SGRDP on which the more recent work is based.

Under the auspices of the SGRDP, the basic Detection, Diagnosis, and Remediation (DDR) design was established and the initial implementations of the AMI data collector (developed by USC Information Sciences Institute (ISI), the DDR database, the DDR data monitors, and some prototype detectors were completed.

Under the auspices of the LADWP-funded effort, the design of the fault containment zones and components, along with the Detection, Diagnosis, and Recovery systems within the cyber security landscape were refined to support additional capabilities, many of the existing components were improved, and some new components were implemented (new detectors and diagnosticians, alert emitter, simulated data injector, and DDR local visualization tools). This work builds on the prior SGRDP work to advance LADWP's goals in the area of securing the smart grid.

Use of the Terms Partner and Partnership

The use of the words "partner" and "partnership" herein is intended to indicate a mutually beneficial collegial relationship, rather than a partnership as defined under state law.

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1 Executive Summary

The Department of Energy (DoE) awarded the Los Angeles Department of Water and Power (LADWP) funding for a Smart Grid Regional Demonstration Program (SGRDP) in response to DoE Federal Opportunity Announcement DE-FOA-0000036. The project's original budget was $120.56 million where 50% were to be funded by DOE, and 50% were to be funded by LADWP as cost share.

LADWP collaborated with its project partners to carry out this demonstration in the designated areas to include two university campuses – the University of California, Los Angeles (UCLA) and the University of Southern California (USC) – surrounding neighborhoods, City of Los Angeles facilities, and LADWP power system test labs. The last project partner, Jet Propulsion Laboratory (JPL) was responsible for the cyber security aspects of the project. The program's use cases provided insightful information to understand triggers for customers, distributors, and generators to adapt their behavior which aid in reducing system demands and costs, increasing energy efficiency, and increasing grid reliability.

SGRDP has demonstrated innovations in key areas of smart grid technologies and behavioral studies which were carried out in parallel to identify the behavioral determinants essential for successful adoption of Smart Grid technologies and improved energy usage patterns.

The overall project focused on the following four interrelated demonstration projects:

- Demand Response (DR) - Consists of integrated demonstration of load curtailment strategies through utilizing test bed sites such as USC campus, UCLA dormitories. This effort also provides investigation and pilot execution of a full range of user infrastructure environments including residential, commercial, institutional, medical, retail, and light industrial.

- Electric Vehicle (EV) Integration into the LADWP Grid - demonstrates smart charging; battery aggregation and backfill; renewables and EV battery integration; demonstration of a fully operational microgrid; and a demonstration using car sharing programs at USC and UCLA.
  For the purposes of the SGRDP, LADWP uses the term microgrid to represent a specific area of the larger service territory which is being used to demonstrate one or more functions of the smart grid. For these demonstrations, there are no microgrids which have the capability to operate as an island from the overall electric grid.

- Customer Behavior (CB) - demonstrates a comprehensive portfolio of studies and surveys to determine the impact of smart grid communication systems and processes on customer usage patterns; energy savings resulting from the use of smart grid enabled interfaces, pricing options and programs; and effective messaging strategies and incentives to educate and interest different target customer groups regarding Electric Vehicles.

- Next-Generation Cyber Security - demonstrates technologies to show: Grid Resilience - showing how the Smart Grid can operate resiliently against physical and cyber-attacks; Operational effectiveness - to demonstrate a complete cyber security testing approach for components and

installed systems; and Redefinition of the security perimeter to demonstrate new cyber security measures that address the expansion of this perimeter by smart grid technologies to the meter in residential and commercial sites.

SGRDP was implemented in stages:

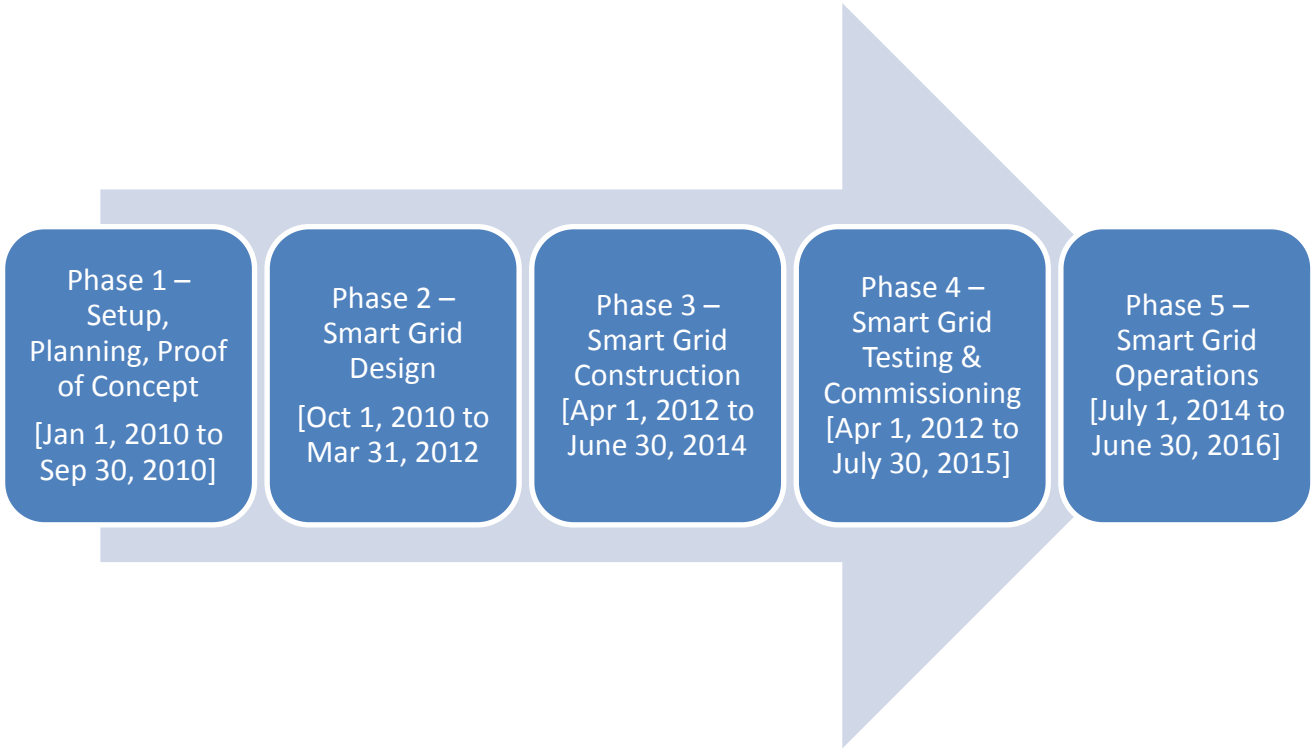


Figure 1: Stages of SGRDP

In phase 1, LADWP updated the Project Management Plan (PMP), developed the interoperability and Cyber Security Plan, and developed the Metrics and Benefits Reporting Plan. The DOE checked for National Environmental Policy Act (NEPA) compliance and evaluated the developed plans to provide approval to LADWP to proceed to phase 2.

In phase 2, LADWP developed the preliminary designs for Demand Response, Electric Vehicles, Customer Behavioral Studies, and Next-Generation Cyber Security demonstrations. During phase 2, the Cross Project Architecture and System Integration were developed and evaluated. The preliminary design information was provided to DoE and the designs were finalized based on DOE's feedback. Final pricing and proposals were determined and evaluated for the construction phase, where the DOE reviewed the final design and provided approval before the Construction Phase began.

In phase 3, LADWP began to purchase equipment and supplies in accordance with the approved final design and purchasing procedures. Installations and implementation of equipment, instrumentation, software and other supplies for each of the sub-project areas were conducted.

In phase 4, testing and analysis was conducted to determine if the outcomes of the demonstrations were consistent with the expected outcomes defined in the final design. Test plans were reviewed and corrected for deficiencies for all sub-projects.

Demonstrations were conducted in phase 5 for all sub-projects at the demo laboratories and test bed site. Operations outcomes were monitored, evaluated, and reported.

2 Key Objectives

2.1 Objectives

The objective of this program was to demonstrate Smart Grid and Energy Storage technologies in the Los Angeles area that present a suite of use cases applicable to the LADWP service area and transferrable for national implementation and replication.

The goal was to use the demonstrations' output to provide the optimal amount of information necessary for customers, distributors, and generators to change their behavior in a way that reduces system demands and costs, increases energy efficiency, optimally allocates and matches demand and resources to meet that demand, and increases the reliability of the grid.

The anticipated benefits of a smart grid and of energy storage technologies are reduced emissions, lower costs, increased reliability, greater security and flexibility to accommodate new energy technologies, including renewable, intermittent and distributed generation sources.

This report provides insight into the implementation, operation, and analytical progression of demonstrated technologies. It also discusses discussion of grid functionality and benefits of Smart Grid that were anticipated and enabled by the demonstration and describes the impact metrics for assets that will be deployed as permanent part of the utility system, and summarizes the interoperability and cyber security effort performed during the award period and the associated results. A comprehensive discussion of lessons learned is also included in the report that would help open the market for viable, commercially available Smart Grid (SG) solutions, representing the state of the industry such that similar large-scale Smart Grid infrastructure projects can be implemented across the nation.

2.1.1 Advanced Metering Infrastructure Demonstration Objectives

1) Provide a mechanism and strategy to carry out DR actions.
2) Provide a mechanism for managing the integration of renewable energy resources.
3) Provide a mechanism for managing EV charging and customized EV electric power billing.
4) Provide metering of power usage at various service connections.
5) Provide capability for timely feedback to customers related to power usage profile.
6) Enable timelier billing of customers for power.
7) Enable improved power outage detection and management.
8) Enable scheduled/remote service connection and disconnection to manage move-outs and payment delinquencies.

2.1.2 Demand Response Demonstration Objectives

1) Provide power system control operations with real-time information through the usage of visualization tools for making outage and load management decisions.

2) Implement a LADWP web portal powered by smart meter data, feedback tools and customized messaging to provide services for customers to become actively involved in changing their energy use habits.
3) Implement a program tested with residential customers who are interested in participating in HAN demonstrations to help define future state offerings for Home Energy Management (HEM) and Automate Demand Response (ADR.)
4) Implement Building-to-Grid (B2G) energy management and conduct DR test to optimize load reduction and minimize building occupant negative impacts.
5) Demonstrate an integrated SG infrastructure that can accept DR control signals from LADWP and perform targeted load curtailment across campus.

2.1.3 Customer Behavior Demonstration Objectives

1) Understand the key decision making factors essential to the adoption and use of customer-side energy management technologies.
2) Identify the most effective public outreach and communications approaches to stimulate customer energy usage awareness and improve customer energy use patterns for load management.
3) Increase energy use awareness through interactive software and applications.
4) Conduct behavioral studies to understand the most effective communication, technology, and energy use mechanisms to reduce barriers to adoption of customer-side energy management technologies.
5) Plan and implement public outreach campaigns to promote acceptance of smart meters and related technology, and incorporate tailored messages that are informed by SGRDP CB survey results.
6) Involve customers in the design, development, and evaluation of new utility service offerings in applications/tools for energy visualization and management, and new DR services/programs offered as part of SGRDP.

2.1.4 Electric Vehicle Demonstration Objectives

1) Monitor chargers, power usage, and EV usage
2) Apply charged EVs to maintain grid integrity
3) Integrate EVs with LADWP grid
4) Evaluate Smart-charging of EVs and charging stations
5) Evaluate the ability of the Smart Grid infrastructure to project the integrity of customer, configuration, and audit data

2.1.5 Cyber Security (CS) Demonstration Objectives

1) Develop security services for all major components of the SGRDP that are resistant to external and internal threats.
2) Develop a capability for identifying threats and implementing appropriate remediation.
3) Identify an appropriate containment capability for unseen attacks.

4) Develop an extensible security solution that can be updated to resist new threats as discovered.
5) Implement a security system that supports security event monitoring and information management throughout all major components of the SGRDP system.
6) Demonstrate an intrusion detection capability with low false-positive error rates.
7) Be able to scale operating environments larger than SGRDP
8) Perform interoperability when necessary with commercial security products and systems.

3 SGRDP

3.1 Background

LADWP is the largest municipal utility in the United States. It was established in 1902 to deliver water to the City of Los Angeles. Electric distribution began in 1916. Its service territory covers 465 square miles and serves 3.8 million residents and businesses. LADWP employs more than 8,800 workers and has an annual budget of about $4.9 billion.

In 2010, LADWP produced its power Integrated Resources Plan (IRP). This plan provides a 20-year framework to ensure LADWP will meet the future energy needs of its ratepayers. Through an IRP, utilities forecast the demand for energy and determine how that demand will be met.
The 2010 IRP was guided by the following key objectives:

- Maintain a high level of electric service reliability
- Maintain competitive rates
- Exercise environmental stewardship

For the IRP, LADWP's goal—and primary challenge—is to develop a long-term resource plan that is informative, sensitive to the local and regional economy, and adaptable to changes in state and federal regulations, fuel prices, and advances in power generation technologies. An important component off this plan will be leveraging opportunities offered by Smart Grid (SG) technology. Hence, LADWP has a keen interest in leveraging what functions existing SG technology can offer and shaping the next generation of SG technologies.

USC supported SGRDP by bringing sophisticated facilities operations, technical research, and socio-economic research communities to understand, evaluate, and assist in deploying Smart Grid Technologies and services proposed in this demonstration program. The University operates an unusually broad mix of facility types that was used as a project test bed.

UCLA faculty and staff brought substantial expertise in the area of novel wired and wireless communication networks for open and scalable Smart Grid communications and technology architectures. The UCLA campus provided an additional test bed location that includes research laboratories, classrooms and administrative facilities, student and faculty housing, the UCLA hospital and a cogeneration power plant supplying heat and electricity to more than 25 million square feet of office space.

JPL is a federally funded research and development center and National Aeronautics and Space Administration (NASA) field center. JPL brought extensive expertise in the research and development of cybersecurity and Smart Grid communications technologies, such as the complex model development for the detection, diagnosis, and remediation of cyber-attacks.

The key to an effective implementation of the SGRDP was the creation of a secure, scalable, standards-based, and interoperable cyber-physical system architecture. The goal of SGRDP was to demonstrate SG technologies that embody essential and salient characteristics and present a suite of use cases for national implementation and replication.

3.2 Key Statistics

Workforce	8,800 employees
Area Served	465 square miles
Population Served	Over 3.8 million residents Power Customers: 1.4 million in Los Angeles; 5,000 in the Owens Valley
Power System Fiscal Year 2013-2014 Budget	Total: $3.9 billion $1 billion for operations and maintenance $1.5 billion for capital projects $1.4 billion for fuel and purchased power
Total Megawatts Capacity	Over 7,300 megawatts from a diverse mix of energy resources
All-Time Peak Demand	6,396 megawatts (September 16, 2014) (instantaneous peak)
Power Use for Fiscal Year ending June 2013	
Residential	8.4 million megawatt-hours
Commercial	12.8 million megawatt-hours
Industrial	1.9 million megawatt-hours
Other	0.4 million megawatt-hours
Overhead Transmission Circuits	3,507 miles (spanning five Western states)
Underground Transmission Circuits	124 miles
Overhead Distribution Lines	6,800 miles
Underground Distribution Cables	3,597 miles
Distributing Stations	162
Receiving Stations	21
Substructures	50,636
Distribution Utility Poles	321,516
Pole Mounted Capacity Banks	3,166
Utilitarian Streetlights	29,550
Distribution Transformers	126,000

Table 1: Facts & Figures on LADWP

3.3 System Overview

SGRDP demonstrated innovations in key areas of Smart Grid technologies. It used the USC and UCLA campuses and surrounding neighborhoods, city facilities, and LADWP labs as testing grounds to prove the technologies and architectures. Figure 2 below shows the locations of the testing areas for the Program.

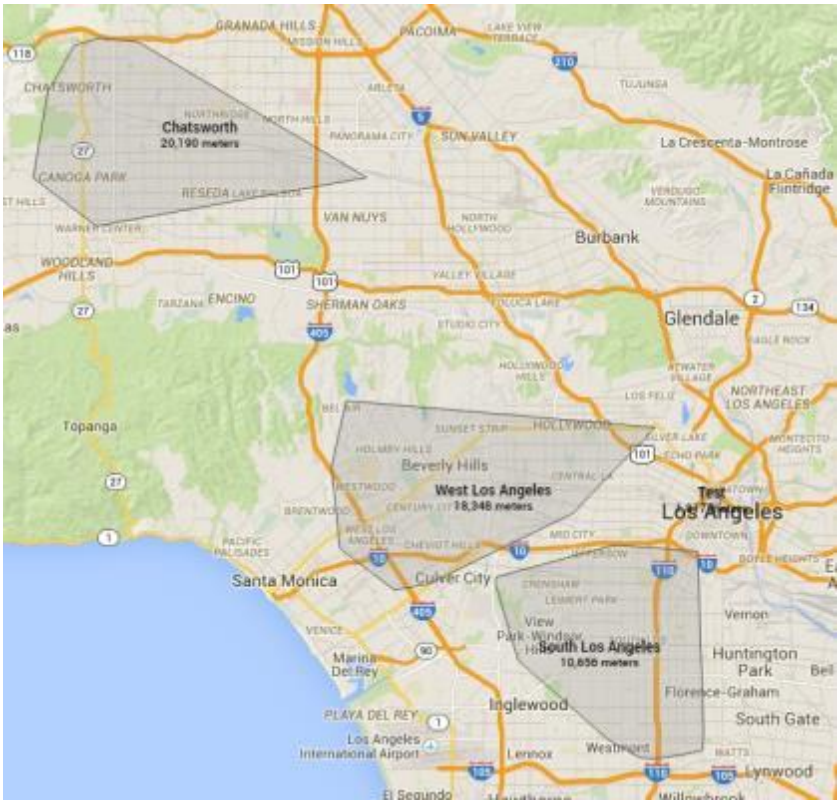


Figure 2: Demonstration Locations

The following table displays the systems that were used in SGRDP:

Systems	AMI	DR	CB	EV	CS
Demand Response Automation Server		X			
CB Web Portal			X		
Demand Response Automation Server DRDR6 -		X			
DR Decision Support (DDS)		X			
Demand Response Automation Server (DRAS)		X			
Demand Response Management System (DRMS)		X			

Elpis2 (K-GRID)	X				
DKUS/SES	X				X
Data Repository		X		X	
CB Portal Application			X		
Headend	X				
Itron CE	X				
SOA	X				
MDM	X	X			
CC&B	X				
CG-NMS	X				
OMS	X				
Distribution Management System				X	
Facility Management System		X			
Security Information and Event Management (SIEM)					X
Active Directory					X
Certicom	X				X
CS Firewall					X

Intrusion Prevention System					X
Detection, Diagnosis and Remediation (DDR)					X
File Integrity Policy System					X
EV Control Center				X	
Smart Demand Response Management System (SDRMS)		X			
Pi Historian	X			X	

Table 2: List of implemented systems for SGRDP relative to each sub-project

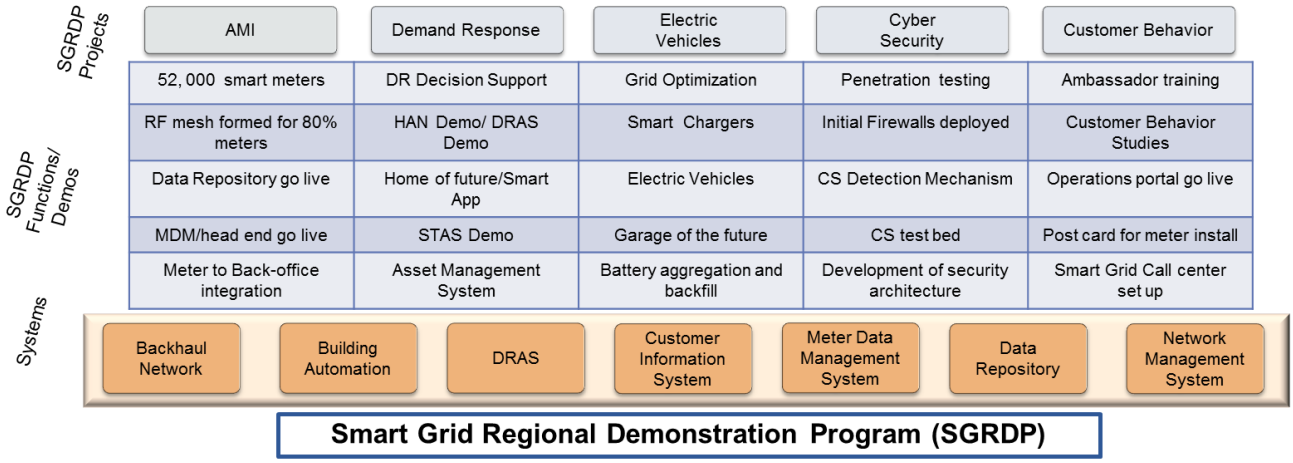


Figure 3: Matrix of systems and demonstrations by project

SGRDP included the following five interrelated demonstration projects and technologies:

3.3.1 Advanced Metering Infrastructure

The AMI demonstration provided the advanced metering infrastructure, which included smart metering, communications network, and the back office operations and applications. This infrastructure enabled and supported all SGRDP projects in terms of Consumption data, power service data, and customer-related information. The data provided by smart meters were used by various components of the DR, CB, and EV projects. Revenue meters have been installed in a number of microgrids (areas with two-way communication with meters, and capability to deploy demand response) within the LADWP service area. The locations of such deployments were selected in a way to allow a diversity of demographics and

environments that reflect other utilities within the nation. Stored meter-read data is transmitted periodically through a communications network to the back office where the data is collected into databases and used for customer billing and other utility services and operations.

Site surveys were conducted to ensure that the signal strength and bandwidth capacity of the proposed communication solution locations could meet the AMI project requirements. A Communication Design Package was developed to include a map that showed the location and the specification of the meter to be installed, along with cellular, risk, and security information. All the deployed meters were compatible with the existing back office system. The interfaces for Headend - Meters and Headend - Smart Grid Gateway (SGG) were tested.

3.3.2 Electric Vehicle

The EV project displayed the integration of EVs into the LADWP-managed grid, which includes smart charging, aggregated battery storage for vehicle fleets as a distributed storage option with a "garage of the future" demonstration, a fully operational EV microgrid with communications and grid management system, and EV sharing programs at USC and UCLA, two urban test beds which represented different user demographics, driving patterns, and grid specifications for accommodation of EVs. Smart charging includes monitoring of chargers, power usage, and EV usage Battery aggregation and backfill; more specifically, the viability of applying charged EVs for maintaining grid integrity related to renewable portfolio and resource planning goals. A fully operational microgrid with Substation and Distribution Automation (DA) was deployed with a car/ride share program at LADWP, including Smart-charging of EVs and charging stations in the LADWP Service Grid impact and power study to demonstrate the ability of the SG infrastructure to protect the integrity of customer, configuration, and audit data.
A "grid impact study" was also performed in order to analyze the effect of connection of the EV chargers to the grid at different timings.

3.3.3 Customer Behavior

A portfolio of customer behavioral studies was deployed in order to study, monitor, and stimulate customer energy usage patterns by providing timely power usage data; to optimize energy savings through the implementation of DR efforts via smart grid-enabled interfaces; and to encourage customers to participate in DR programs and adopt EVs via targeted messaging and outreach efforts. A comprehensive set of surveys were conducted at the beginning and end of SGRDP to assess customers' attitudes, beliefs and assumptions regarding energy consumption. CB demonstrations experimented with different outreach messaging and incentives (via the USC Microgrid) to explore energy usage during demand response events. The USC Microgrid is separate from the LADWP service area and allowed for experimentation to be undertaken in isolation without impacting the LADWP service area. The USC Microgrid area is comprised of the USC campus and associated facilities.

3.3.4 Cyber Security

The CS project demonstrated next-generation CS technologies on Grid resilience which displayed how the Smart Grid (SG) can operate resiliently against physical and cyber-attacks, obtain operational effectiveness through the demonstration of a complete CS testing approach for components and installed systems, and redefinition of the security perimeter. The CS project also showed new CS measures capable of addressing the expansion of this perimeter by SG technologies that extent to the meter in residential and commercial sites.

3.3.5 Demand Response

The DR project was comprised of integrated Smart Grid technology and operations for DR (e.g., to manage load in peak demand conditions). DR test bed sites and tools were chosen to investigate a full range of user infrastructure environments, including residential, commercial, institutional, medical, retail, and light industrial. Forecasting power consumption of the system based on historical trends and the system's characteristics was part of the DR's approach to monitor and manage the system's load. DR technologies were designed and deployed on the customer and utility sides of the meter for active monitoring and dynamic control of electricity usage.

On the customer side, building and home automation, customer load response, customer behavior, smart charging and discharging of EVs and Micro-grids created new opportunities and new challenges for grid operations and optimization. On the utility side, analytics based on real-time and historic energy consumption data, real-time distribution system data, and customer behavior information provided utility control center operators with forecasting and visualization tools to increase the accuracy and reliability of load management decisions. Smart meters and advanced building and home automation systems provide customers with unprecedented levels of convenience and control to manage how and when energy is used.

3.4 SGRDP Systems Data Flow

The figure below illustrates the data flow in between SGRDP systems:

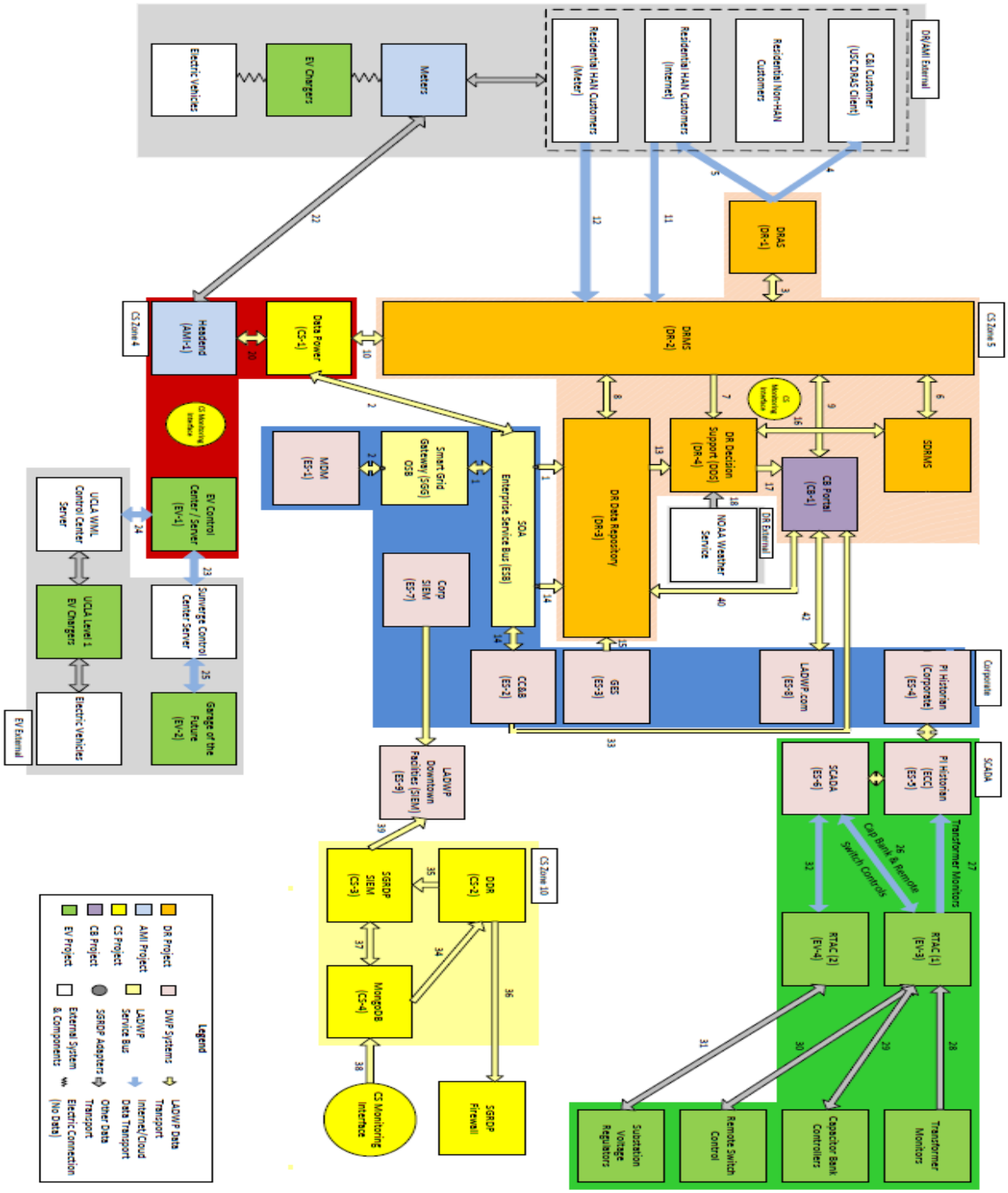


Figure 4: SGRDP Systems Data Flow updated 8/18/16

3.5 SGRDP Function Definition

The table below depicts the devices and their functionality relative to the sub-project demonstrations:

Project	Device	Category	Primary Function	Description
EV/DR	DA/SA Equipment	Customer usage	Power System Monitoring	Monitor and remote control 4.8 kv pole-top capacitors
EV	DA/SA Equipment	Customer usage	Power System Monitoring	Monitor 4.8 kv pole-top transformers
EV	DA/SA Equipment	Customer usage	Power System Monitoring	Monitor and remote control 34.5 kv pole-top line switches
EV/DR	DA/SA Equipment	Customer usage	Power System Monitoring	Monitor and remote control 4.8 kv substation voltage regulators.
EV	Garage of the future	Customer usage	Load Management	1-way and 2-way chargers
EV	Garage of the future	Customer usage	Load Management	Integrated EV and solar
EV	Garage of the future	Customer usage	Load Management	Community storage
EV	Garage of the future	Customer usage	Load Management	Battery cycling
EV	Garage of the future	Customer usage	Load Management	Battery aggregation
AMI	AMI Meters - Electric	Customer usage	Management	Receive and process connect and disconnect controls.
AMI	AMI Meters - Electric	Customer usage	Monitoring	Send meter outage event messages to CC&B and OMS

AMI	AMI Meters - Electric	Customer usage	Management	Receive and forward DR Event objects between Service Gateway and DRAS for EV customers
AMI	AMI Meter - Water	Customer usage	Data Measurement	Sample and store water usage measurements
AMI	Collector / Repeater	Customer usage	Data Measurement	Communication infrastructure for RF meter implementation
AMI	PQ Meters	Customer usage	Data Measurement	Sample and store PQ measurements
EV	Level 2 Chargers	Customer usage	Monitoring	Provide load profiling for customer accessible level 2 chargers
EV	Level 3 Chargers	Customer usage	Monitoring	Provide load profiling for DWP personnel accessible level 3 chargers
EV	Customer - Electric Vehicle	Customer usage	Data Analysis	Research and Development of rideshare
CS	Web services security appliance	Infrastructure protection	Infrastructure Management	Secure, manage and mediate inbound and outbound web traffic
CS	Identity Management/Policy servers	Infrastructure protection	Infrastructure Management	Provide authorization services and facilitates tracking. Serves as a policy repository and a decision point for mediating access to data and authority to issue commands throughout the SG demonstration system.
CS	Network Firewalls or Firewall Appliances	Infrastructure protection	Infrastructure Management	Control network traffic.
CS	Intrusion detection systems	Infrastructure protection	Infrastructure Management	Monitor network and/or system activities

CS	Intrusion detection systems	Infrastructure protection	Infrastructure Management	Create intrusion reports
CS	Security Information and Event Management (SIEM)	Infrastructure protection	Infrastructure Management	Analyze security alerts
CS	Security Information and Event Management (SIEM)	Infrastructure protection	Infrastructure Management	Log security data
CS	Security Information and Event Management (SIEM)	Infrastructure protection	Infrastructure Management	Create reports for compliance purposes
CS	Virtual Private Networks (VPN)	Infrastructure protection	Infrastructure Management	To protect communication in the AMI and DA network
CS	Security Simulator	Infrastructure protection	Data Analysis	Simulate system for evaluation of data security
DR	DEW	Customer usage	Distribution System Modeling	Evaluate data and actions to correct distribution system
EV	DEW	Customer usage	Distribution System Modeling	Evaluate the impact of distributed generation, storage and new demand technologies
DR	DR Decision Support (DDS)	DR Event	Pre DR Event Customer load forecasting	Forecasts energy consumption at the customer level
DR	DR Decision Support (DDS)	DR Event	Customer Selection	Use customer load forecast and their prior response to DR Events to optimally select the customers that will receive a DR Signal
DR	DR Decision Support (DDS)	DR Event	DR Event Validation	Compile customer DR Event compliance statistics to refine future DR consumer selection
DR	DR Decision Support (DDS)	DR Event	Curtailment Adaptation	Compare the predicted and actual energy consumption of a customer and use that information to update the

				customer's willingness to comply
DR	Demand Response Automation Server (DRAS)	DR Event - Configuration	Utility Configuration	Enrollment of DR Program C&I participants
DR	Demand Response Automation Server (DRAS)	DR Event - Configuration	Customer Configuration	DR Program Management
DR	Demand Response Automation Server (DRAS)	DR Event	Event Initiation	Utility system operator schedules event
DR	Demand Response Automation Server (DRAS)	DR Event	Event Initiation	Utility system operator initiates event
DR	Demand Response Automation Server (DRAS)	Customer usage	DR Event - Residential	Process DR Event object for residential customers through AMI and Internet
DR	Demand Response Automation Server (DRAS)	Customer usage	DR Event - C&I	Process DR Event object for C&I customers
DR	Smart Demand Response Management System (SDRMS)	Customer usage	DR Monitoring	Geospatial visualization of DR operational parameters
DR	Smart Demand Response Management System (SDRMS)	Customer usage	Event Management	Analytic geospatial visualization of DR operational parameters
DR	Smart Demand Response Management System (SDRMS)	Customer usage	Event Management	Plan DR Event and schedule
DR	Data Repository	Data Storage	Data Management	Working copy of customer preferences
DR	Data Repository	Customer usage	Data Management	Record historical event objects into Data Repository which is the system of record for DR

DR	Customer - Service Gateway	Customer usage	Data Management	Store customer preferences
DR	Customer - Service Gateway	Customer usage	Load Management	Process DR Event objects at customer's premise
DR	Customer - Programmable Communicating Thermostats (PCT)	Customer usage	Smart Appliance Management	Process load management signal
DR	Customer - Refrigerator	Customer usage	Smart Appliance Management	Process load management signal
DR	Customer - Clothes Washer and Dryer	Customer usage	Smart Appliance Management	Process load management signal
DR	Customer - Smart Plug, Power Strip	Customer usage	Smart Appliance Management	Process load management signal
DR	Customer - In Home Display (IHD)	Customer usage	Data Management	Customer display for preferences and event participation
DR	Customer - Browser (e.g., IE, Firefox, Chrome)	Customer info	Data Management	Customer display for event participation, thermostat
DR	Customer - Browser (e.g., IE, Firefox, Chrome)	Customer info	Data Management	Customer display for preferences, smart appliances
CB	CB Web Portal server	Customer info	Data Management	Customer display for real-time energy usage and event participation
CB	CB Web Portal HEI Program	Customer Education Tools	Influence Customer Behavior	Tools provided via web portal to educate the customer on the information available and their home energy use

CB	Outreach	Customer Education Tools	Customer education/customer outreach	Raise customer awareness using lessons learned from other utilities, social psychology, and marketing principles to conduct a successful meter rollout. This includes but is not limited to: - analyzing available behavioral data - developing campaign - mailing (or posting) literature
CB	Utility Education	Utility Education Tools	Social Media Data Mining	Use current literature and social media platforms to capture spontaneous public dialogue related to Smart Grid. This includes but not limited to: - analyzing available behavioral data - developing campaign - mailing (or posting) literature
CB	Utility Study	DR Event - Campus/Commercial	DR Event Improvement	Surveys to explore residential, commercial, and industrial preferences for energy management services and attitudes. This includes but not limited to: - analyzing available behavioral data - developing campaign - mailing (or posting) literature
CB	Utility Education	Utility Education Tools	Surveys	Surveys to explore customer preferences for energy management services. This includes but not limited to: - analyzing available behavioral data - developing campaign - mailing (or posting) literature
AMI	AMI Meters - Electric	Customer usage	Data Measurement	Sample, collect, and store power, energy, and demand. For C&I, also VAR, PF,

				voltage, current.
AMI	AMI Meters - Electric	Customer usage	Load Management	Provide meter connect and disconnect controls
AMI	AMI Meters - Electric	Customer info	Alert Collection	Provide alert/alarm messages
AMI	AMI Meters - Electric	Customer usage	Load Management	Responds to Demand Response events
AMI	AMI Meters - Electric	Customer usage	Monitoring	Sample and store power, energy, and demand
AMI	AMI Meters - Electric	Customer usage	Data Measurement	Sample, collect, and store power, energy, and demand. For C&I, also VAR, PF, voltage, current

Table 3: SGRDP Function Definition

3.6 SGRDP Metering Functional Organization Chart

The figure below lays out the functional organization chart for smart metering.

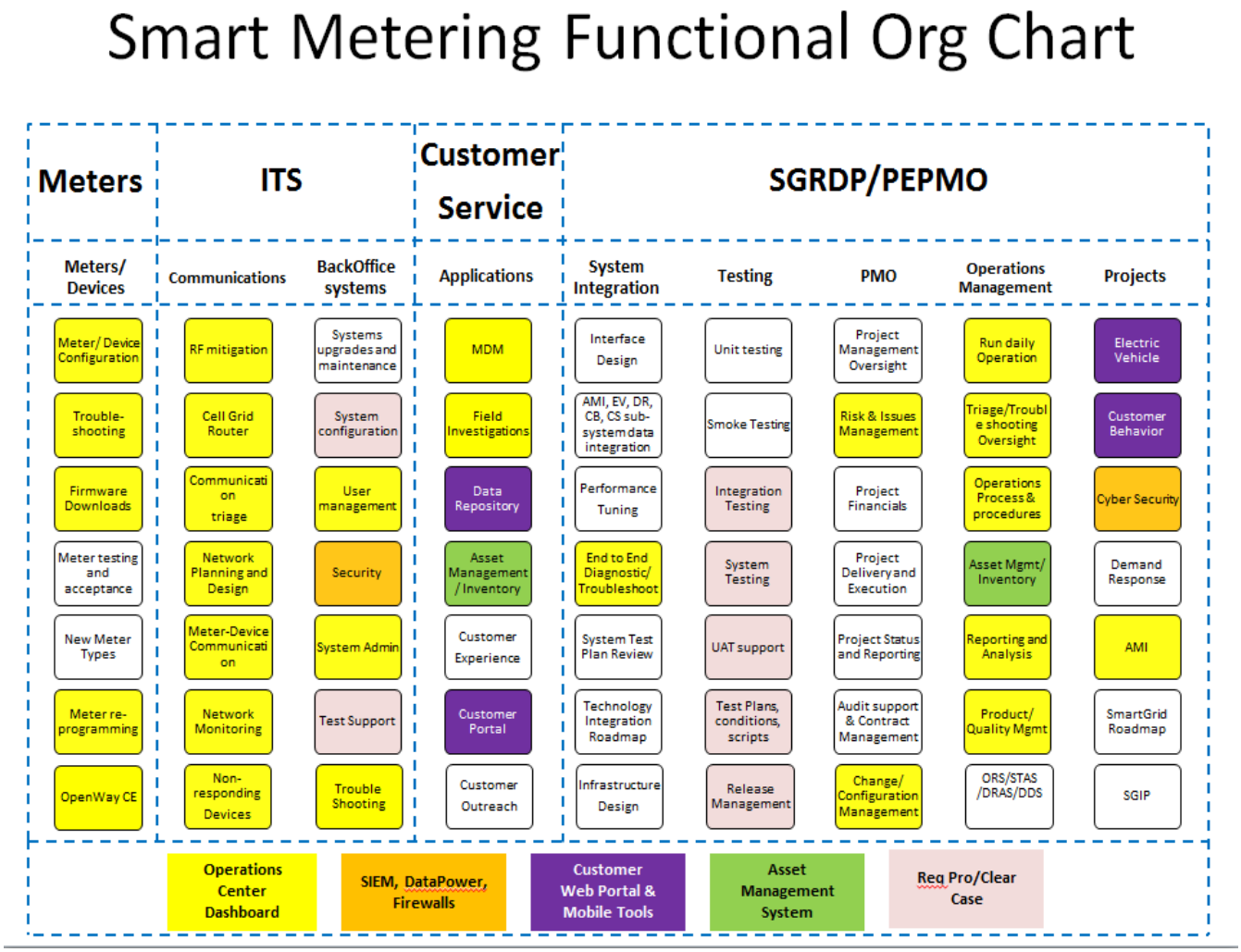


Figure 5: SGRDP Metering Functional Organization Chart

3.7 SGRDP Architecture and Data Management

SGRDP Demonstration system detailed layering is depicted below:

Smart Grid Applications	*Layer 3*
Data Collection and Distribution	*Layer 2*
Legacy Grid and Infrastructure	*Layer 1*

Figure 6: SGRDP Architecture Layers

The Legacy Grid, or existing power grid, and Infrastructure's main functions are grouped as the lowest layer which includes power generation, transmission, and distribution. Functions that support the advanced data network responsible for generation, data collection, distribution, and storage reside in the central (middle) layer. The top layer has the most complex functions where it utilizes the data from the middle layer and implements the advanced features which differentiate a smart grid from the legacy grid.

3.7.1 AMI

The AMI system architecture is shown below:

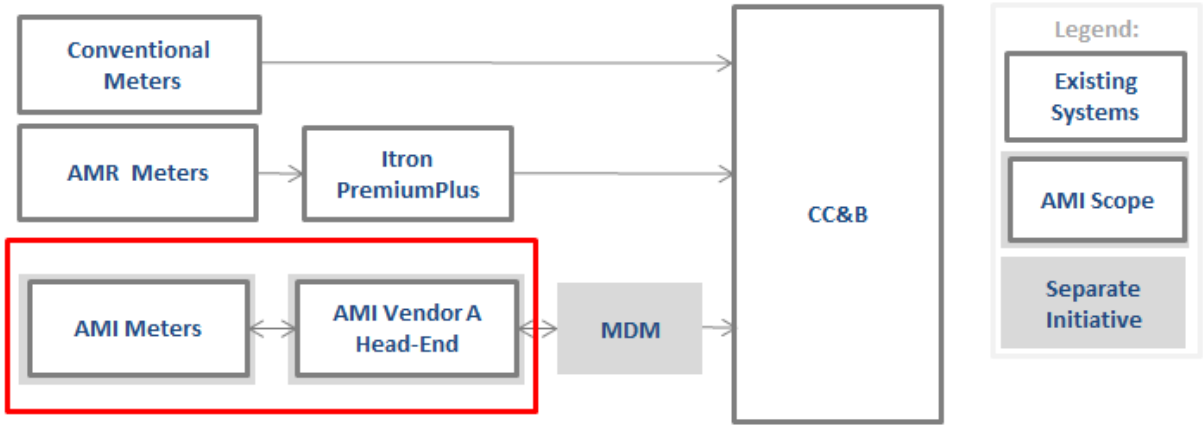


Figure 7: AMI system architecture

AMI collected data from Smart Meters, Cisco Connected Grid Routers (CGRs), Meter Data Management (MDM), Head-End, and Range Extenders to compile the following summaries:

- Meter Data
- Network Communication/Performance Data
- Communications Statics
- Event/Issue Log
- Periodic Summary/Report

All AMI meters send data to the Head-End collection point via the communication network "cloud." Depending on the type of data, the Head-End collection point directs the data to the Meter Data Management System (MDMS).

3.7.2 DR

The DR system architecture is shown below:

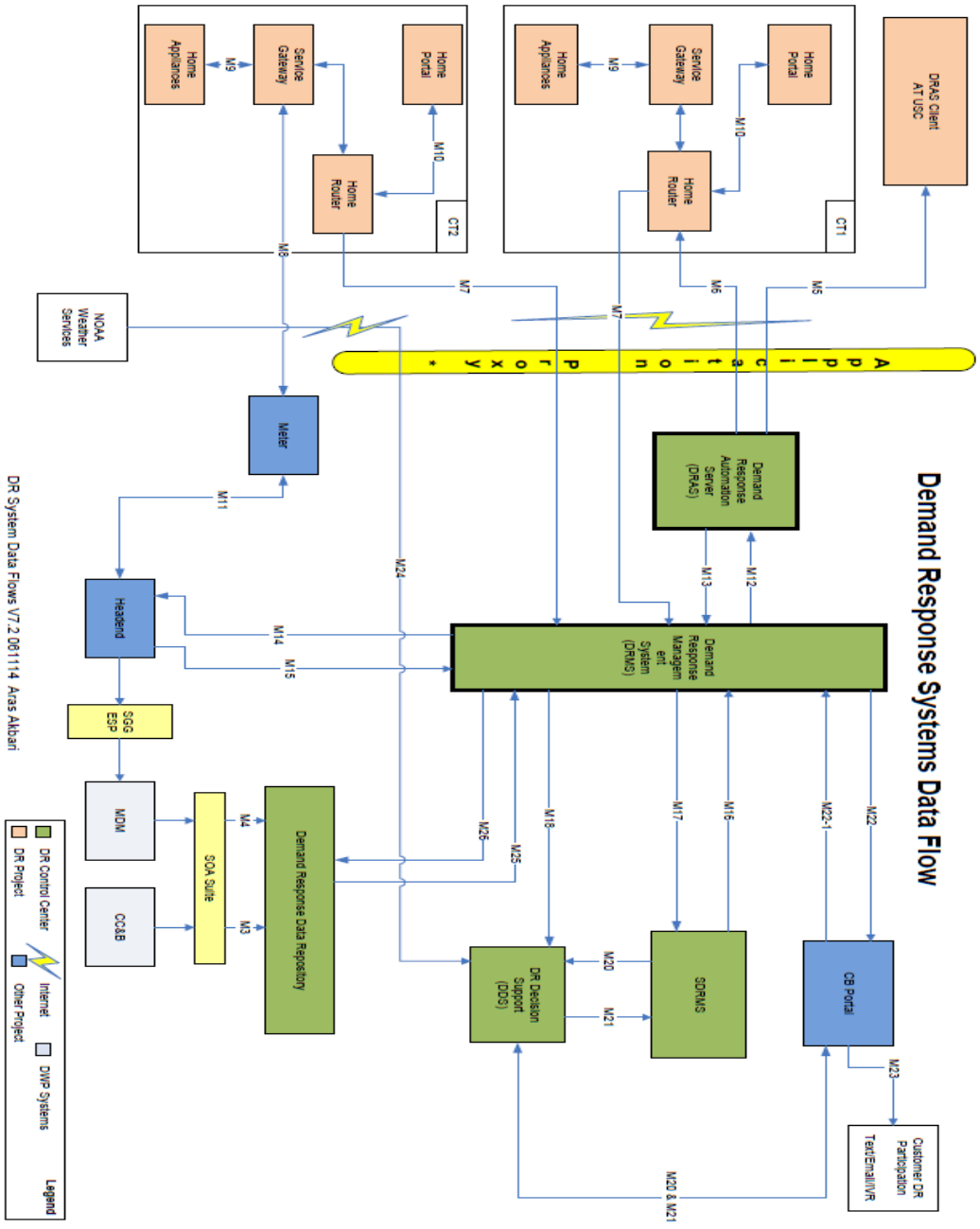


Figure 8: DR system data flow architecture

DR collected data from Data Repository, Customer Care & Billing (CC&B), Demand Response Automation Server (DRAS), UCLA, and USC to compile the following summaries to address DR/CB use cases:

- Customer Consumption (Meter) Data
- Customer Preference/ Profile Data
- DR Events Data from DRAS
- Smart Appliance Consumption Data (HAN ADR)
- FMS Consumption Data (Voluntary / Automated Demand Response (ADR))

3.7.3 CB

The CB infrastructure is shown below:

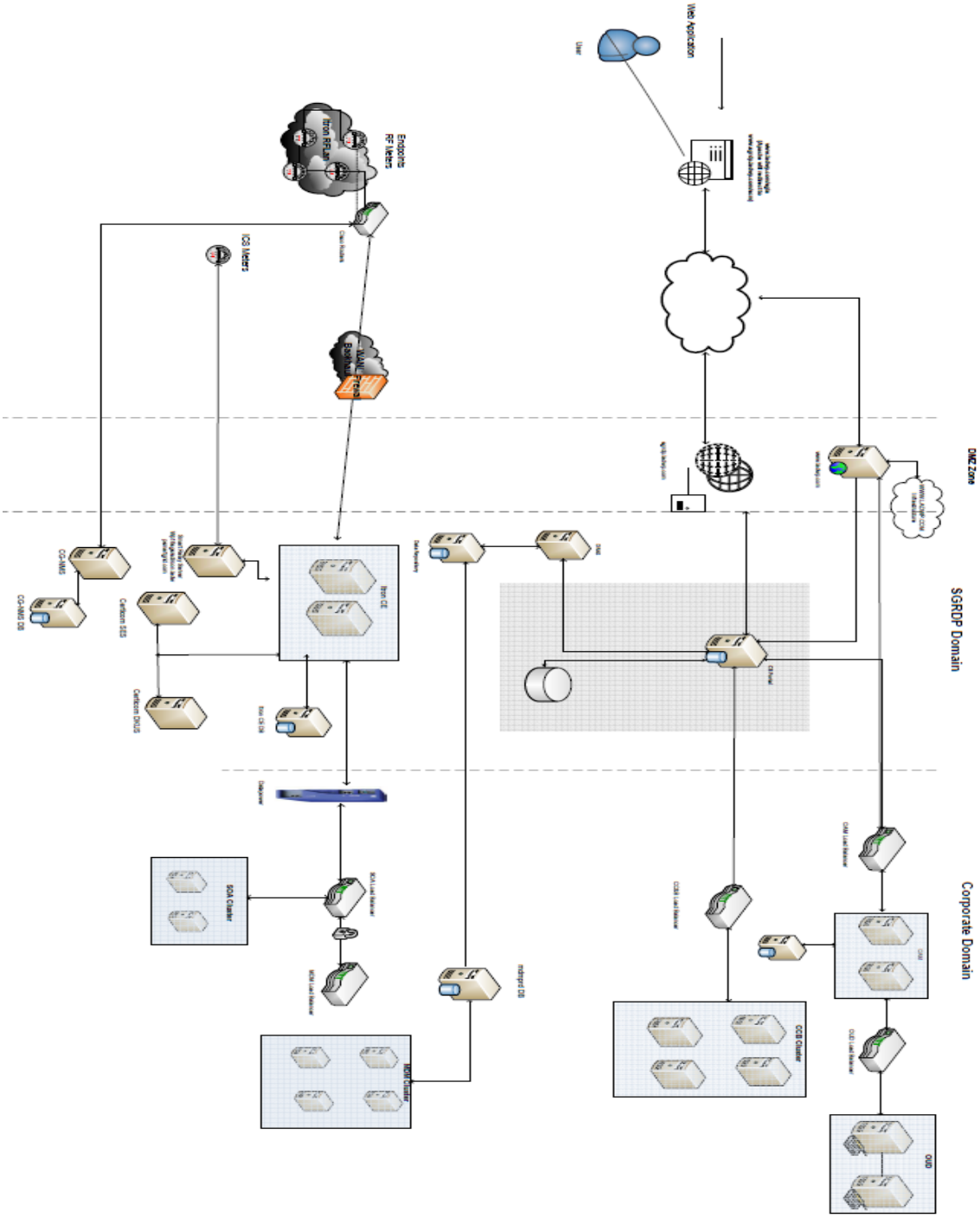


Figure 9: CB system architecture

Some of the CB demonstrations and deliverables are based on the deployment of the web portal. The web portal accesses 3 databases in LADWP:

- AMI network – source of meter data for the Web Portal. Electricity use data is measured in 15 minute-intervals and is available for download once per day.
- Customer Information System – Customer Relationship Management (CIS-CRM) database – an existing database that stored LADWP basic customer data. Later, LADWP chose Oracle's Customer Care and Billing (CC&B) as the CIS solution.
- Data repository – database for all other data required to be stored for the CB experiments.

3.7.4 EV

The figure below illustrates PI/ Historian is the main data store for EV project.

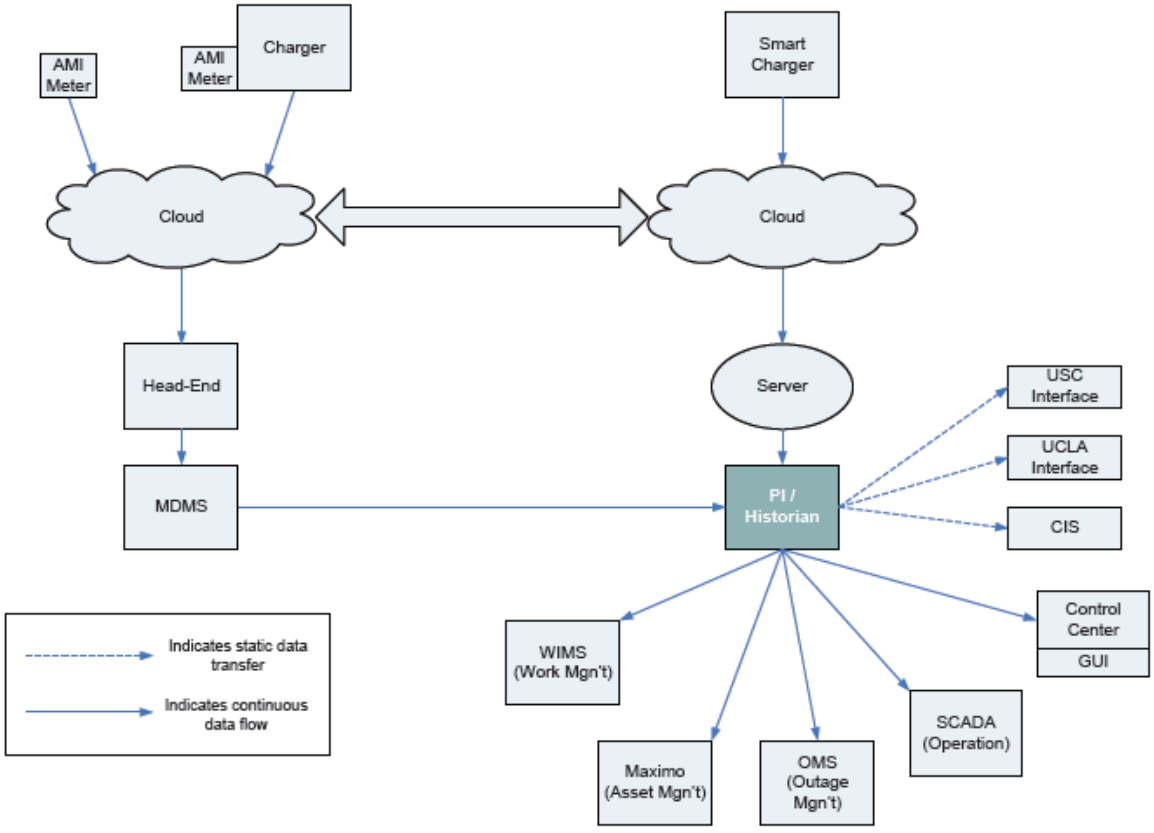


Figure 10: EV system architecture

PI / Historian serves as one of the main data stores for all time-based Supervisory Control and Data Acquisition/Energy Management Systems (Supervisory Control and Data Acquisition (SCADA)/Energy Management Systems (EMS)) data at LADWP.

Data Repository maintains data for four major components.

• DRAS
• Service Gateway
• Web Portal
• SDRMS

EV collected data through Data Repository, FleetCarma, Fleet Driver Form/radio frequency identification (RFID), Temperature Sensor, Garage of the Future EMS, SCADA/Energy Control Center (ECC)/PI-Historian/Grid 20-20, and UCLA EV Control Center in order to accumulate the following summaries to address EV use cases:

- Charger Status/Accumulative Charging Data
- EV Vitals
- Charging Scenario
- Photovoltaic Vitals
- Inductive Charging
- CES/Battery Vitals
- Charging/Discharging Results
- Session Parameter Data (Grid-to-Vehicle (G2V)/Vehicle-to-Grid (V2G))
- Distribution Transformer Monitor (DTM)
- Cap Bank Controller
- 34.5kV Switch
- Voltage Regulator
- Feeder Monitor

3.7.5 CS

CS identified the confidentiality, integrity, and resiliency requirement of each SGRDP data flow, described measure that must be applied to each data flow, and incorporated the data flows into the requirements and technologies.

The CS data protection module design consists of the following components:

1. **Function** – supports protected communication between components, signs data, validates the integrity of data and contains a policy enforcement module which checks permissions on access when a security authorization operation is to be performed.
2. **Output** – Consists of encrypted or decrypted data, data to be authenticated, and audit records
3. **Input** – Consists of Security policies, data encryption/decryption/verification requests
4. **Dependencies** – Requires Cryptographic techniques that support other CS components, including identity Management, and Privacy/Policy

The Data Project component applies different protection to data as controlled by policies based on data classification.

CS data was collected through Firewall logs, Information Sciences Institute (ISI), and Cisco Grid-Network Management System (CG-NMS)/Itron Collection Engine (CE) to compile CS Event logs, intrusion alerts, and security scenarios.

3.8 SGRDP Milestones

Below is a list of SGRDP milestones:

1. Complete Purchasing
2. Complete Smart Grid Demo Installation / Construction
3. Complete Demo Operations Phase
4. Closeout Subcontracts
5. Complete Smart Grid Preliminary Design
6. Complete Smart Grid Final Design
7. Develop CS Containment Infrastructure (CS)
8. Complete CS Monitor and Controls (CS)
9. Complete Basic DDR System (CS)
10. EV Charger Deployment (EV)
11. Complete Garage of the Future (EV)
12. Complete EV Distribution Automation (EV)
13. DR Smart Appliances Deployment (DR)
14. DR Data Repository Deployment (DR)
15. DR Automation System Deployment (DR)
16. Complete LADWP Customer Baseline Surveys (CB)
17. Complete Web Portal (CB) - Phase 0
18. Complete Web Portal (CB) - Phase 1
19. Finish SGRDP Customer Outreach (CB)
20. Develop Smart Grid Infrastructure (AMI)
21. Complete AMI Acceptance Test (AMI)

3.9 SGRDP Cost

The project's baseline budget is shown below:

Baseline Budget		
Los Angeles Department of Water and Power (LADWP) Smart Grid Regional Demonstration Project	**$**	**120,560,000.00**
Customer Behavior	$	6,303,592.76
Cyber Security	$	13,858,974.80
Demand Response	$	50,873,420.54
Electric Vehicle	$	20,180,652.05
PEPMO	$	29,343,359.85

Table 4: Baseline Budget

The actual final cost is pending to be finalized based upon Department of Energy's approval on the final invoices.

The actual cost per project is shown below:

Final Cost		
Los Angeles Department of Water and Power (LADWP) Smart Grid Regional Demonstration Project	**$**	**116,162,155.45**
Customer Behavior	$	5,415,356.57
Cyber Security	$	13,221,982.94
Demand Response	$	42,283,069.82
Electric Vehicle	$	21,003,265.58
PEPMO	$	34,238,480.55

Table 5: Final Cost

The overall breakdown of cost for SGRDP by category is shown below:

Category	Expenditure	
Personnel	**$**	**10,213,658.87**
Fringe Benefits	**$**	**7,218,084.18**
Travel	**$**	**385,129.20**
Equipment	**$**	**3,894,316.09**
Supplies	**$**	**2,325,301.58**
Contractual	**$**	**90,595,830.38**
Construction	**$**	**65,456.74**
Other Direct Costs	**$**	**1,464,378.42**
Total Project Costs	**$**	**116,162,155.45**
DOE Share	**$**	**60,280,000.00**
LADWP Share	**$**	**55,882,155.46**

Table 6: Cost Breakdown

4 Build Metrics

The final build metrics for period of performance ended on June 30, 2016 are shown in the tables below.

4.1 AMI and Customer Systems Assets

Build Metrics	(Planned)	(Deployed)
AMI End Points Installed	**Project**	**System**
End points (meters) installed and operational	51,123	51,123
# Residential customers w/ AMI	50,133	50,133
# Commercial customers w/ AMI	1,230	1,230
# Industrial customers w/ AMI	0	0

Table 7: Number of meters installed for each type of customers

Implemented Meter Features	Project	System
Reading interval for residential meters (minutes)	15	15
Reading interval for commercial meters (minutes)	15	15
Reading interval for industrial meters (minutes)	0	0

Table 8: Reading intervals by customers

Features	Implemented?	
Remote Connection/Disconnection	Yes	
Outage Detection/Reporting	Yes	
Power quality monitoring	Yes	
Tamper detection	Yes	
# of meters with Remote Connect/Disconnect	50,133	50,133
# of meters implemented with Outage Reporting	51,363	51,363
# of meters implemented with Power Quality Measurement	1,230	1,230
# of meters implemented with Tamper Detection	50,123	50,123

Table 9: Features that were implemented on the deployed AMI meters

AMI Installed Cost	Project Funded	Cost Share
Back office Systems	$ 300,366	$300,366
Customers with active accounts	$ 147,500	$ 147,500
AMI Smart Meters	$ 5,053,242	$ 5,053,242
Other Cost	$ 3,500,000	0

Table 10: AMI Installed Cost

Descriptions of implemented features:

Backhaul Communication Network

Where physical conditions permitted, the project deployed an RF system which uses the LADWP's fiber network as a backhaul mechanism. This network functions as the wide area network (WAN) to transfer the data from designated substations to the back-office, located at the DWP's headquarters. RF backhaul is operational.

Meter Communication Network

For meters that could not access the RF backhaul communication network, the project deployed an RF system. Other locations used a public cellular technology (point-to-point communication) as the solution. The communication solutions are the 'media' for two-way communication between the meters and the back-office. Cellular technology is operational.

Home Area Network

The HAN or service gateway deployment allows customers to set preferences for when and how their on-site equipment uses energy. The software uses these preferences to exert control over smart devices within the home. The software also responds to Demand Response commands issued by the utility based on customer preferences. This is operational.

Headend System

The purpose of the head-end system is to interface the advanced metering infrastructure (AMI) system with the meter data management (MDM) which is used as part of the back-office. As different metering solutions have been designed with different firmware, various head-end systems will be used to accommodate two-way communication between the meters and the back-office. This is operational.

Meter Data Management System

The MDM functions as the central repository for collected metering data. LADWP has chosen Oracle's Utilities as the MDM solution. The MDM can collect the data (through the head-ends) and perform the required data analysis for monitoring and managing the metering system throughout the company. The MDM will also be a central element in the automated billing process.

Meter data analysis systems

The back-office (which includes the Meter Data Management) will be programmed to perform data analysis on the collected metering data. This will include trend analysis, estimation, validation, load forecasting, and comparison between usages in various regions.

Other Meter Feature

Besides remote communication with meters, the advanced meters can provide signals or alarms to notify the back-office about an outage, as well as certain situations or scenarios as it relates to the electric service. Voltage fluctuations, tampering, poor power quality, failure in communications, or problem with the meter's hardware are examples of situations that can be reported to the back-office through meter alarms. The meter can also perform bi-directional metering for the customers that generate power. The meters will also provide remote connect/disconnect capability.

AMI Enterprise Integration	Implemented?
Billing System	No
Customer Information System	Yes
Outage Management System	Yes
Distribution Management System	Yes
Other Enterprise System	Yes

Table 11: Systems integrated with AMI Enterprise

Description of systems integrated with AMI and/or to be integrated with AMI:

Billing System

The Customer Information System is a custom software application which performs all billing for all customers except the 100 major Industrial customers. These industrial customers are billed using the MV90 system. The MV90 billing system uses consumption and/or demand data collected from advanced meters, and rate information, to generate appropriate billings.

Customer Information System

The Customer Information System is a tailored custom software application which is used as central repository for customer information. LADWP has chosen Oracle's Customer Care and Billing (CC&B) as the CIS solution. The CIS will be notified of customers' outages as well.

Outage Management System

CGI's PragmaLINE Outage Management System is used to gather information on the power outages in the system and notify appropriate parties to take necessary actions to restore the power.

Implemented Customer Systems	Project	System
In-Home display installed	0	0
Direct Loan Control Devices installed	22	22
Programmable Communicating Thermostats installed	1,100	1,100
Smart Appliances installed	36	36
Energy Management Devices/Systems installed	29	29
Other Device - Light Control Units installed	15	15

Table 12: Metrics of implemented customer systems

Web Portal	Implemented?	
Web Portal is in production?	Yes	
Access	Project	System
Customers with access	50,837	50,837
Customers with active accounts	1,033	1,033

Table 13: Web portal status

Customer System Installed Costs	Project Funded	Cost Share
Back Office Systems	$0	$0
Web Portal	$ 4,600,000	$0
In-Home Displays	$0	$0
Direct Loan Control Devices	$ 1,461	$ 1,461
Smart Appliances	$ 8,911	$ 8,911
Programmable Communicating Thermostats	$ 402,664	$ 402,664
Cost of other devices installed Light Controls	$ 2,121	$ 2,121
Other Cost	$0	$0

Table 14: Customer System Installed Costs

Direct Load Control Devices
Where technically possible, the project will have direct control over customer electric vehicles.

Programmable Communicating Thermostats
The project will be providing customers with programmable thermostats which will communicate through the Home Area Network.

Smart Appliances
The project will support the deployment of Smart Appliance at customer homes. These will be controlled using the HAN/service gateway.

Energy Management Systems
The university participants of the project have Energy Management Systems. As part of the project, these systems will receive and react to Demand Response commands.

Other Devices
The project will support the deployment of Light Control Units at customer homes. These will be controlled using the HAN/service gateway.

Web Portal
As part of the project, SG customers were given access to a Web-based interface where they could view their current energy usage, receive billing information, compare energy usage to neighbors, evaluate potential savings by switching rates, and adjust usage preferences. Additionally, building energy usage kiosks/web dashboards are available for USC Microgrid participants.

4.2 AMI and Customer Programs

Implemented Rate Plans	Implemented?
Flat Rate Pricing Program Available?	**No**

	Project	System
Flat Rate: # customers with access	0	0
Flat Rate: # customers enrolled	0	0

Table 14 Flat Rate Program status

	Implemented?
Flat Rate with Critical Peak Pricing Program Available?	**No**

	Project	System
Flat Rate with Critical Peak Pricing: # customers with access	0	0
Flat Rate with Critical Peak Pricing: # customers enrolled	0	0

Table 15: Flat Rate with Critical Peak Pricing Program status

	Implemented?
Flat Rate with Peak-Time Rebate Program Available?	**No**

	Project	System
Flat Rate with Peak-Time Rebate: # customers with access	0	0
Flat Rate with Peak-Time Rebate: # customers enrolled	0	0

Table 16: Flat Rate with Peak-Time Rebate Pricing Program status

	Implemented?
Tiered Rate Pricing Program Available?	**Yes**

	Project	System
Tiered Rate: # customers with access	50,837	1,302,772
Tiered Rate: # customers enrolled	50,837	1,302,772

Table 17: Tiered Rate Pricing Program status

	Implemented?
Tiered Rate with Critical Peak Pricing Program Available?	**No**

	Project	System
Tiered Rate with Critical Peak Pricing: # customers with access	0	0
Tiered Rate with Critical Peak Pricing: # customers enrolled	0	0

Table 18: Tiered Rate Pricing Program status

	Implemented?
Tiered Rate with Peak-Time Rebate Program Available?	**No**

	Project	System
Tiered Rate with Peak-Time Rebate: # customers with access	0	0
Tiered Rate with Peak-Time Rebate: # customers enrolled	0	0

Table 19: Tiered Rate Peak-Time Pricing Program status

Description of implemented Tiered Rate with Critical Peak Pricing program:

Tiered Rate with Critical Peak Pricing

There are 3 tiers. The levels of the tiers are customer location dependent.

	Implemented?
Time of Use Rate Pricing Program Available?	**Yes**

	Project	System
Time of Use Rate: # customers with access	50,837	1,302,772
Time of Use Rate: # customers enrolled	0	22,938

Table 20: Time of Use Rate Pricing Program status

	Implemented?
Time of Use Rate with Critical Peak Pricing Program Available?	**No**

	Project	System
Time of Use Rate with Critical Peak Pricing: # customers with access	0	0
Time of Use Rate with Critical Peak Pricing: # customers enrolled	0	0

Table 21: Time of Use Rate with Critical Peak Pricing Program status

	Implemented?
Time of Use Rate with Peak-Time Rebate Program Available?	**No**

	Project	System
Time of Use Rate with Peak-Time Rebate: # customers with access	0	0
Time of Use Rate with Peak-Time Rebate: # customers enrolled	0	0

Table 22: Time of Use Rate with Peak-Time Rebate Pricing Program status

Description of implemented Time of Use Rate program:

Time of Use Rate

This will allow customers to plan their electric usage, considering the rate structure for different times of a day or different days of a week.

	Implemented?
Real-time Pricing Program Available?	**No**

	Project	System
Real-time Pricing: # customers with access	0	0
Real-time Pricing: # customers enrolled	0	0

Table 23: Real-time Pricing Program status

	Implemented?
Real-time Pricing with Critical Peak Pricing Program Available?	**No**

	Project	System
Real-time Pricing with Critical Peak Pricing: # customers with access	0	0
Real-time Pricing with Critical Peak Pricing: # customers enrolled	0	0

Table 24: Real-time Pricing with Critical Peak Pricing Program status

	Implemented?
Real-time Pricing with Peak-Time Rebate Program Available?	**No**

	Project	System
Real-time Pricing with Peak-Time Rebate: # customers with access	0	0
Real-time Pricing with Peak-Time Rebate: # customers enrolled	0	0

Table 25: Real-time Pricing with Peak-Time Rebate Program status

	Implemented?
Variable Peak Pricing Program Available?	**No**

	Project	System
Variable Peak Pricing: # customers with access	0	0
Variable Peak Pricing: # customers enrolled	0	0

Table 26: Variable Peak Pricing Program status

	Implemented?
Pre-pay Pricing Program Available?	**No**

	Project	System
Pre-pay Pricing: # customers with access	0	0
Pre-pay Pricing: # customers enrolled	0	0

Table 27: Pre-pay Pricing Program status

	Implemented?
Net Metering Pricing Program Available?	No

	Project	System
Net Metering Pricing: # customers with access	0	0
Net Metering Pricing: # customers enrolled	0	0

Table 28: Net Metering Pricing Program status

Other program available?	**None**
Rate Decoupling is implemented?	**No**

Table 29: Other program status

4.3 Distributed Energy Resources

	Project	System	*(units)*
Distributed generation: number of units	0	0	*#*
Distributed generation: installed capacity	0	0	*kW*
Distributed generation: total energy delivered	0	0	*kWH*

Table 30: Distributed Generation Status

	Project	System	*(units)*
Energy storage: number of units	1	1	*#*
Energy storage: installed capacity	16	16	*kW*
Energy storage: total energy delivered	0	0	*kWH*

Table 31: Energy Storage Status

	Project	System	*(units)*
Plug-in electric vehicles charging points: number of units	1,038	1,038	*#*
Plug-in electric vehicles charging points: installed capacity	7,972	7,972	*kW*
Plug-in electric vehicles charging points: total energy delivered	0	0	*kWH*

Table 32: Chargers Status

Distributed Energy Resources' (DER) Installed Costs	Project Funded	Cost Share
DER Interface Control Systems	$0	$0
Communications Equipment	$0	$0
DER/(Distributed Generation) DG Interconnection Equipment	$0	$0
Renewable DER	$0	$0
Distributed Generation Equipment	$0	$0

Stationary Electric Storage Equipment	$ 12,050	$ 12,050
Plug-in Electric Vehicles (PEVs)and Charging Stations	$ 1,531,442	$ 1,531,442
Other Costs	$ 900,000	$ 900,000
Other Cost Description	PEVS and Charging Stations installed costs do not include all the labor hours for installation. **Estimates**	

Table 33 : Distributed Energy Resources' Installed Costs

Distributed Generation Interface Description

The project created a "garage of the future" to do a full scale test of the interaction between various technologies and EV's. These technologies include local energy storage and PV generation. Wind based generation was excluded from scope as the blades were damaged and it was determined that a certified source was not available. Therefore, in lieu of delaying the project from getting inspected and approved by Building and Safety, wind turbine was de-scoped from SGRDP.

Implemented Distribution Devices	Units	Project	System
Portion of system with SCADA	%	30	30
Portion of system with Distribution Automation (DA)	%	75	75
Automated Feeder Switches: # of devices installed	#	1	1
Automated Capacitors: # of devices installed	#	0	0
Automated Regulators: # of devices installed	#	0	0
Feeder Monitors: # of devices installed	#	24	24
Remote Fault Indicators: # of devices installed	#	0	0
Transformer Monitor (line): # of devices installed	#	68	68
Smart Relays: # of devices installed	#	0	0
Fault Current Limiter: # of devices installed	#	0	0
Other devices installed: Capacitor Bank Controller	#	6	6
Other devices installed: MSO Controller/Cabinet	#	1	1

Table 34: Distribution Devices

SCADA

The project automated two of LADWP's feeders in order to evaluate the needs and benefits of Distribution SCADA. The project upgraded controls on distribution devices and will also place monitors on distribution transformers. The telemetry from these devices will be sent to a Supervisory Control and Data Acquisition (SCADA) system hosted by a third party provider. 95% of SCADA became operational as of Q3 2014.

Distribution Automation (DA) devices

As part of this project the following devices were installed and tested:

- Distribution transformer monitors (74 pcs)
- Fault Indicators
- Remotely controlled 34.5kv switch
- Remotely controlled cap banks

DA Applications in Operation	In Operation?	Project	System
Fault Location, Isolation, and Service Restoration (FLISR)	No		
Voltage Optimization	Yes	Yes	Yes
Feeder Peak Load Management	No		
Microgrid	No		
Other DA Application	No		

Table 35: DA Applications in Operation

Distribution Systems Installed Cost	Project Funded	Cost Share
Back Office Systems	$0	$0
Distribution Management System	$ 1,002,408	$ 1,002,408
Communications Equipment and SCADA	$0	$0
Feeder Monitor/Indicator	$ 10,420	$ 10,420
Substation Monitor	$0	$0
Automated Feeder Switches	$0	$0
Capacitor Automation Equipment	$0	$0
Regulator Automation Equipment	$0	$0
Fault Current Limiter Equipment	$0	$0
Cost of other devices installed Capacitor Bank Controller	$ 6,000	$0
Cost of other devices installed MSO Controller/Cabinet	$ 35,048	$0
Cost of other devices installed	$ 45,000	$ 0
Other Costs Transformer Monitors	$0	$0

Table 36: Distribution Systems Installed Cost

Voltage Optimization

Using simulation tools we will demonstrate how to coordinate and manage voltage and Volt-Amp Reactance (VAR) to minimize VAR while simultaneously maintain and optimize system voltage. The voltage profile along a distribution feeder and the reactive power are maintained by a combination of voltage

regulators and switched capacitor banks installed at various locations on the feeder and in the substation. Each voltage regulator has a controller that raises and lowers the voltage regulator tap position in response to local voltage and current measurements. Similarly, each capacitor bank has a controller that switches the bank on or off in response to the local measurements. The volt/VAR control application will integrate measurement information from pole-top capacitors, pole-top transformers, voltage regulator, Power Quality (PQ) meters, and AMI smart meters to satisfy voltage limit and VAR requirements, and thus improve the distribution system performance. This will be demonstrated by simulations. The simulated system performance after the correction, in terms of improved and optimized voltage and VAR, will also be visually displayed.

Microgrid

The USC campus microgrid test bed is a smart grid environment with diverse building and people profiles, and provides a controlled setting for conducting experiments and demonstrations. The microgrid has in place its own building automation system (BAS) that allows the facility operators to remotely monitor, control, and communicate with individual buildings, and play the role of a utility operator that can make decisions on demand response optimization on the campus. In addition, the campus is a large private customer of DWP that can receive and enact curtailment strategies during demand response period. The demonstration will show how an integrated smart grid infrastructure can accept demand response (DR) control signals from LADWP and perform targeted load curtailment across campus, while considering the curtailment potential available in buildings across campus and the preferences of the facility users. In addition, this will also demonstrate the microgrid acting as a utility operations center in making DR decisions. This building-to-grid (B2G) technology integration and demonstration at USC is designed to take a major step towards having a facility testbed with commercial loads that can provide detailed energy consumption information to the grid for the purpose of facilitating better grid management.

Outage Management

The availability of smart meter data (or AMI data) in a smart grid allows the data to be processed and analyzed in real-time to help detect an outage and pinpoint the location and cause. The smart meters can act as a “trip wire” system to indicate the loss of power at an end point. They can be programmed to send a “last gasp” alert message when they have lost power, providing the utility with pinpoint accuracy on the power outage and its time of occurrence. The AMI data allow the system operator to “continuously” (every 15 minutes) monitor the supplied voltage and power at each customer’s premise. The Outage Management System (OMS) will get this outage location detection information from the Customer Information System (CIS), together with the circuit information monitored by SCADA, to identify the fault section of the line and the feeder in trouble. In this project, we will demonstrate the feasibility and capability of the monitoring, communication and detection technologies. The occurrence of an outage will be simulated to show-case the effectiveness of the system.

5 Impacts and Benefits

Impact Metrics AMI and Customer Systems

Metrics Related Primarily to Economic Benefits

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Hourly Customer Electricity Usage	kWh $/kWh	Yes	n/a	Current Usage	Decrease	Calculate	1,922.46	1,588.42	-17.38%

Figure 11: Hourly Customer Electricity Usage

Usage 2/1/2015 - 6/30/2016					
2015	Total:	248,300.33	Total:	231,908.93	2016
kWh	Avg:	1,700.69	Avg:	1,588.42	kWh

Figure 12: Usage 2/1/2015 - 6/30/2016

Analysis was conducted on the initial 119 Smart Grid customers who registered for the CB Portal within the first week (1/11/2016 – 1/17/2016) it was deployed. Usage data showed a decrease in energy use for these customers from Feb 2016 – April 2016. Add the weather overlay and even for the majority of days in 2016 which were hotter than 2015 for Feb – April, there is a decline in usage in 2016 as compared to 2015.

Based on this analysis, we can make the assumption that overall the CB Portal added value and contributed in some ways to the curtailment of usage. Refer to the charts shown below.

There is a slight increase in usage for one week in June 2016 vs June 2015 due to temperature.

Customer portal showed a lower usage in 2016 vs 2015 in general and when there is an increase in usage, it's attributed to extreme hot weather patterns.

The average kWh dropped by 112.26 kWh between February to June 2015 and February to June 2016.

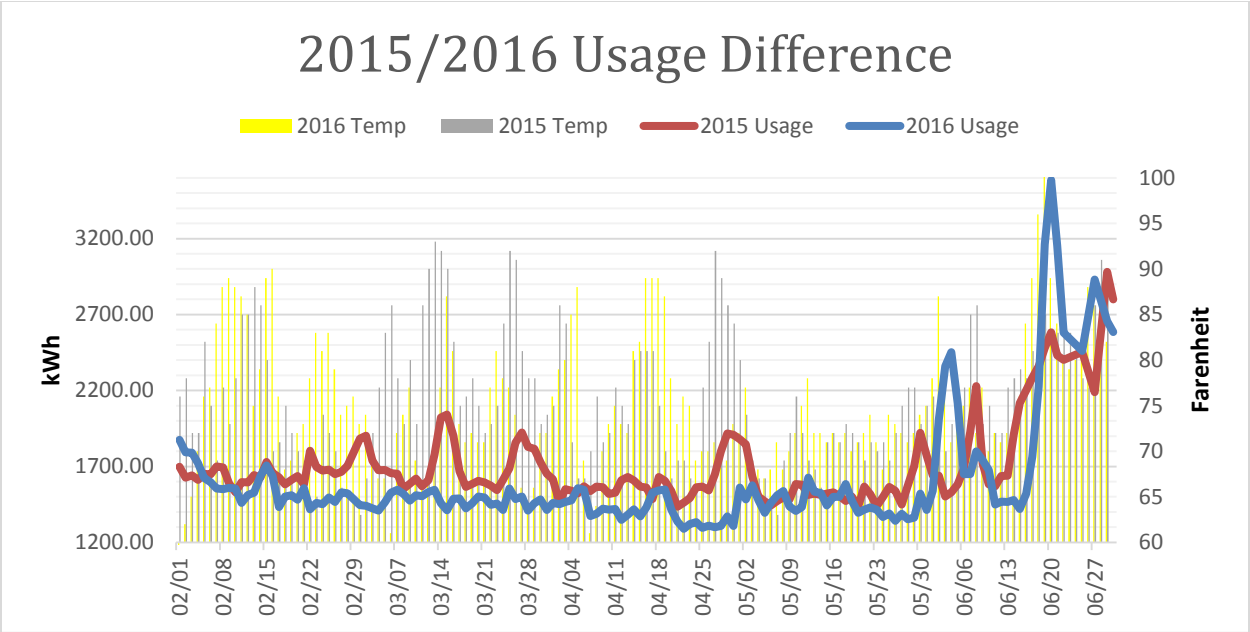


Figure 13: Usage Difference

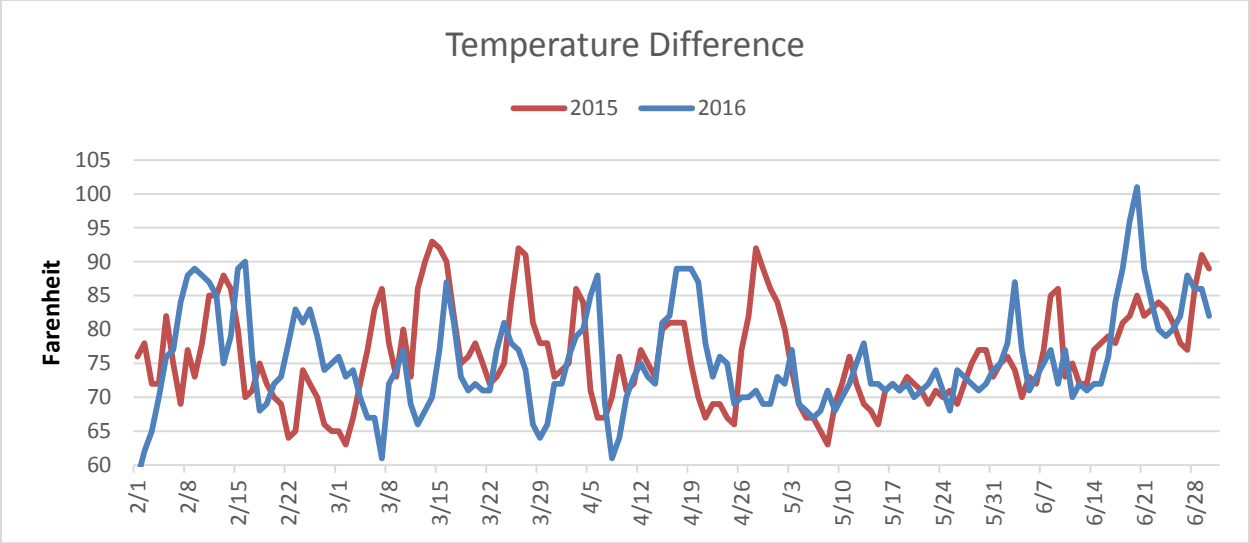


Figure 14: Temperature Difference

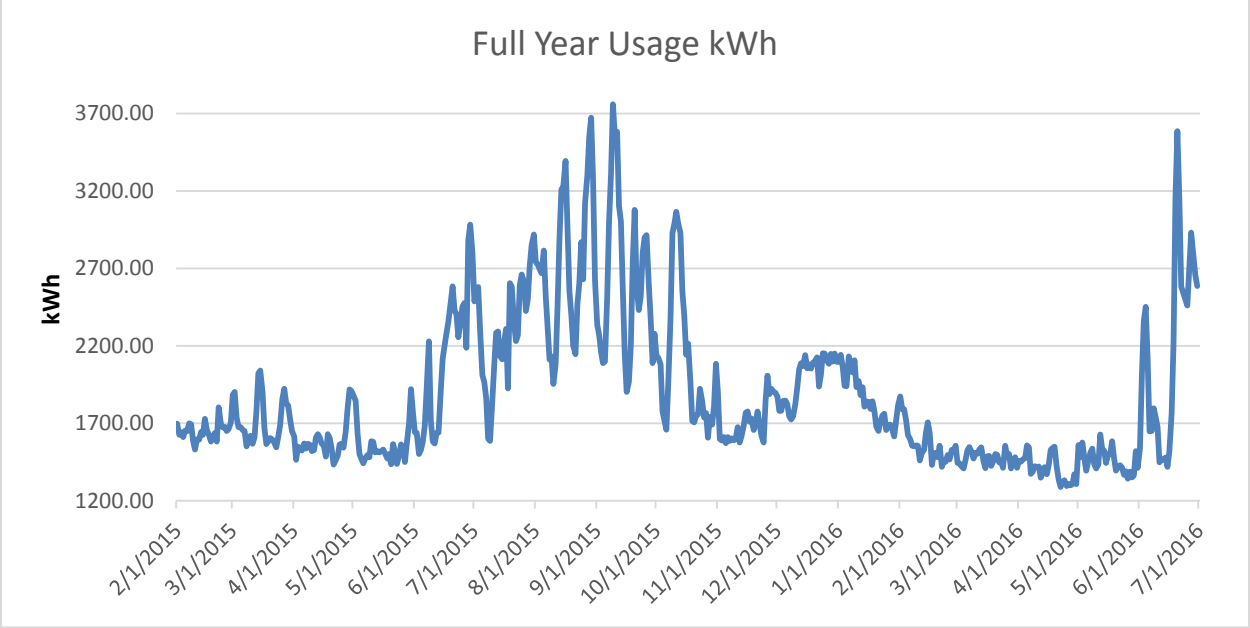


Figure 15: Full Year Usage kWH

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Monthly Customer Electricity Usage	kWh $/kWh	Yes	n/a	Current Usage	Decrease	Calculate	49,172.58	48,830.58	-0.70%

Figure 16: Monthly Customer Electricity Usage

Analysis was done on the first 119 customers that registered for the CB Portal within the first week (1/11/2016 – 1/17/2016). Usage data started to show a decrease from Feb 2016 – April 2016. Based on this analysis, we can make the assumption that overall the CB Portal added value and contributed in some ways to the curtailment of usage. The difference in kWh in 2015 to 2016 for period of January to June was a decrease of 12,659.63 kWh, average decrease was 2,531.93 kWh.

	Total kWh	Average kWh	Temp			
1/1/2015	55,130.29	471.20	72.71	51,362.50	Total 1/15 - 6/15	Before Web Portal
2/1/2015	46,380.53	396.41	74.25	48,830.58	Total 1/16 - 6/16	After Web Portal
3/1/2015	53,554.54	457.73	79.06	**2,531.93**	Difference kWh	
4/1/2015	47,582.67	406.69	75.94	256,812.51	Total 2/15 - 6/15	
5/1/2015	48,172.32	411.73		244,152.88	Total 2/16 - 6/16	
6/1/2015	61,122.46	522.41		12,659.63	Difference	
7/1/2015	67,901.03	580.35				
8/1/2015	77,481.13	662.23		51,362.50	Avg. 2/15 - 6/15	
9/1/2015	79,904.95	682.95		48,830.58	Avg. 2/16 - 6/16	
10/1/2015	65,945.16	563.63		**2,531.93**	Difference	
11/1/2015	51,036.92	439.97				
12/1/2015	58,999.26	504.27				
1/1/2016	60,113.84	513.79	66.03	439.00	Avg. 2/15 - 6/15	Before Web Portal
2/1/2016	48,435.93	421.18	77.48	428.53	Avg. 2/16 - 6/16	After Web Portal
3/1/2016	49,063.17	419.34	72.32	**10.47**	Difference kWh	
4/1/2016	46,493.06	407.83	75.80	2,194.98	Total 2/15 - 6/15	
5/1/2016	45264.918	404.15		2,142.65	Total 2/16 - 6/16	
6/1/2016	54895.8	490.14		52.33	Difference	

Figure 17: Total kWH, Avg kWh, Temp

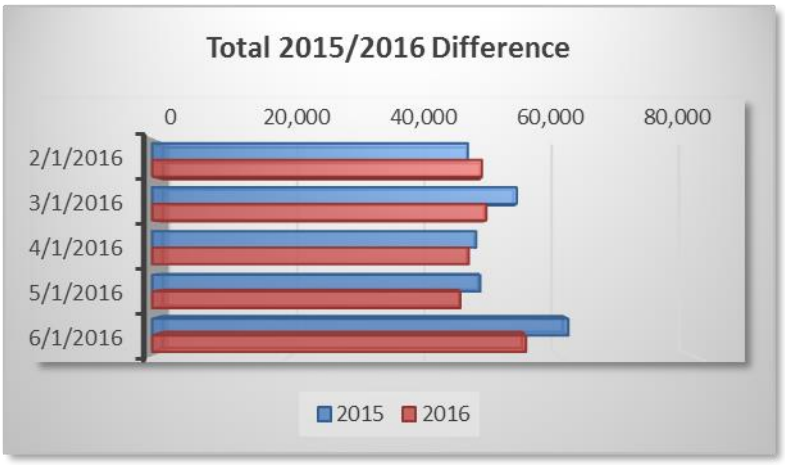


Figure 18: Total kWh (Difference)

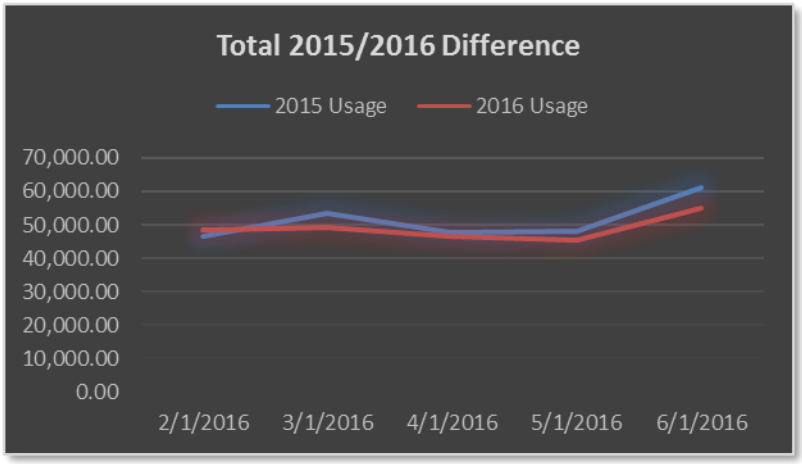


Figure 19: Total kWh (Trends)

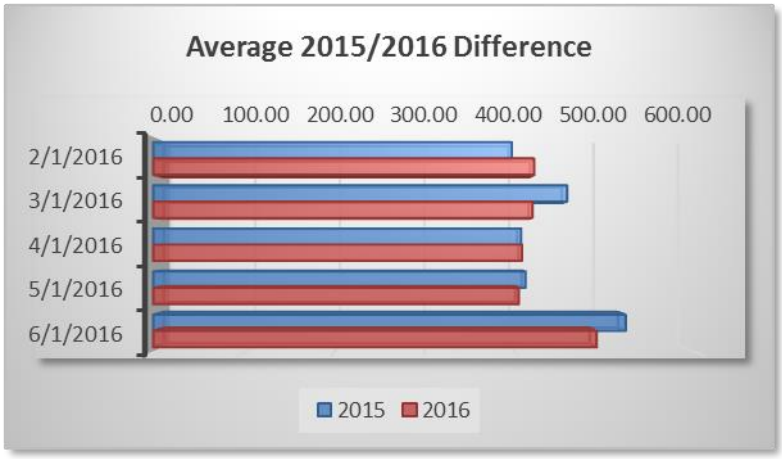


Figure 20: Average kWh (Difference)

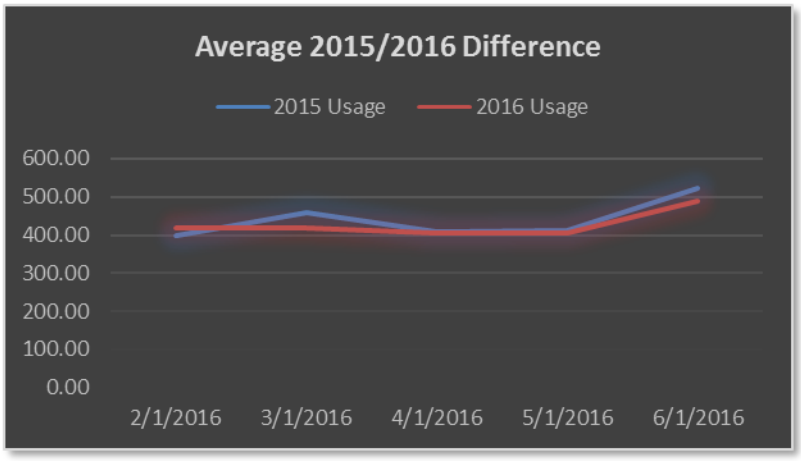


Figure 21: Average kWh (Trends)

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Peak Generation and Mix	MW Mix	Yes	Yes	Current Generation	Decrease	Calculate	7467	8108	8.58%

Figure 22: Peak Generation and Mix

Increase in Peak Generation is due to system wide usage instead of project usage. Project Peak Generation Mix was impossible to calculate. System Wide Peak Generation Mix is shown below:

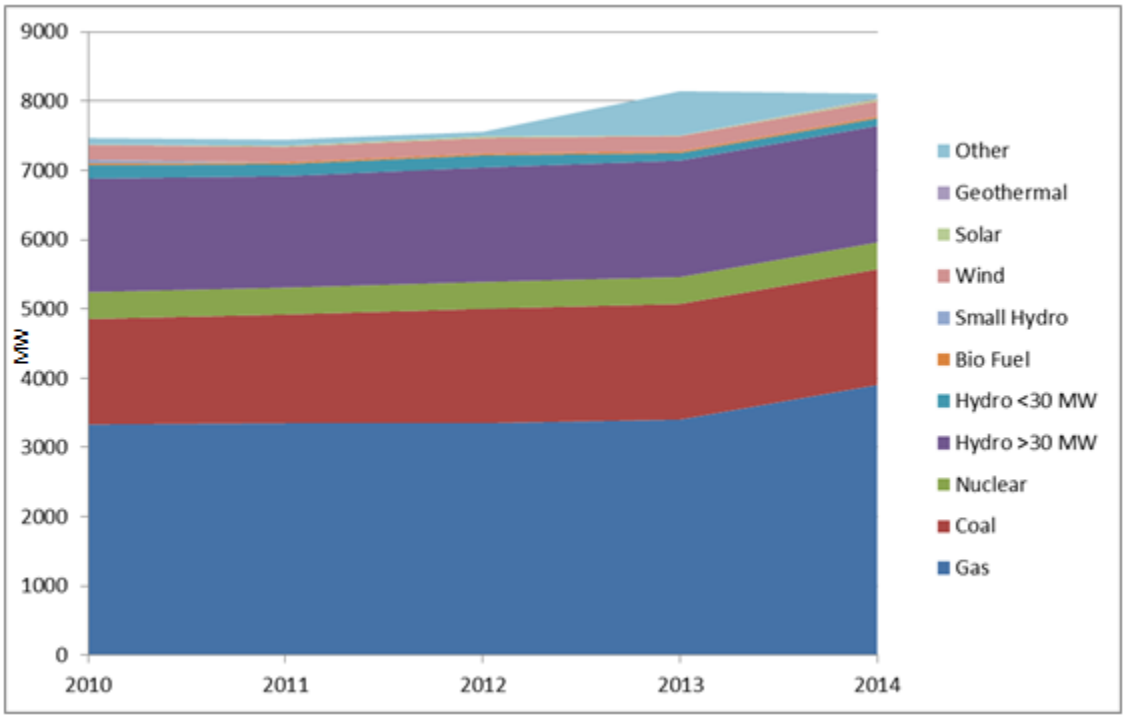


Figure 23: System Wide Peak Generation Mix

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Peak Load and Mix	MW Mix	Yes	Yes	Current Load	Decrease	Calculate	260.74	295.71	13.41%

Figure 24: Peak Load and Mix

Baseline Month	Baseline Year	Comparison Year	2014 Average Peak Load (Wh)	2015 Average Peak Load (Wh)	2016 Average Peak Load (Wh)	Average Peak Load Change (%)
August	2014	2015	356.7806814	414.7835809	Data Unavailable	16.26%
September	2014	2015	303.4128179	435.8349826	Data Unavailable	43.64%
October	2014	2015	330.8834956	376.7867129	Data Unavailable	13.87%
November	2014	2015	187.9377574	218.9562762	Data Unavailable	16.50%
December	2014	2015	269.2218863	253.9470992	Data Unavailable	-5.67%
January	2015	2016	Data Unavailable	233.9098452	234.7762209	0.37%
February	2015	2016	Data Unavailable	184.3555275	241.0118177	30.73%
March	2015	2016	Data Unavailable	219.4077514	189.5724622	-13.60%

Figure 25: Peak Load Data

Based on available data, a peak load of 16 MWh was observed on August 15, 2015 at 4:15pm. The data below is derived from the Peak Load Analysis report and does not reflect a consistent trend in peak load reduction. The table below reflects the average peak load based on the available meter data. The percent of change is calculated by month and compared with available data from the earlier year to the latter year. The baseline is the average of the Wh for the baseline year. The update is the average of Wh for the year following the baseline. The variance percentage is the percentage increase/decrease from the baseline year.

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Annual Generation Cost	$	Yes	Yes	Current Cost	Decrease	Calculate	1,310,000,000	1,400,000,000	6.87%

Figure 26: Annual Generation Cost

Increase in Annual Generation Cost is due to system wide cost instead of project cost. Project Generation Cost was impossible to calculate. The annual generation cost is shown below.

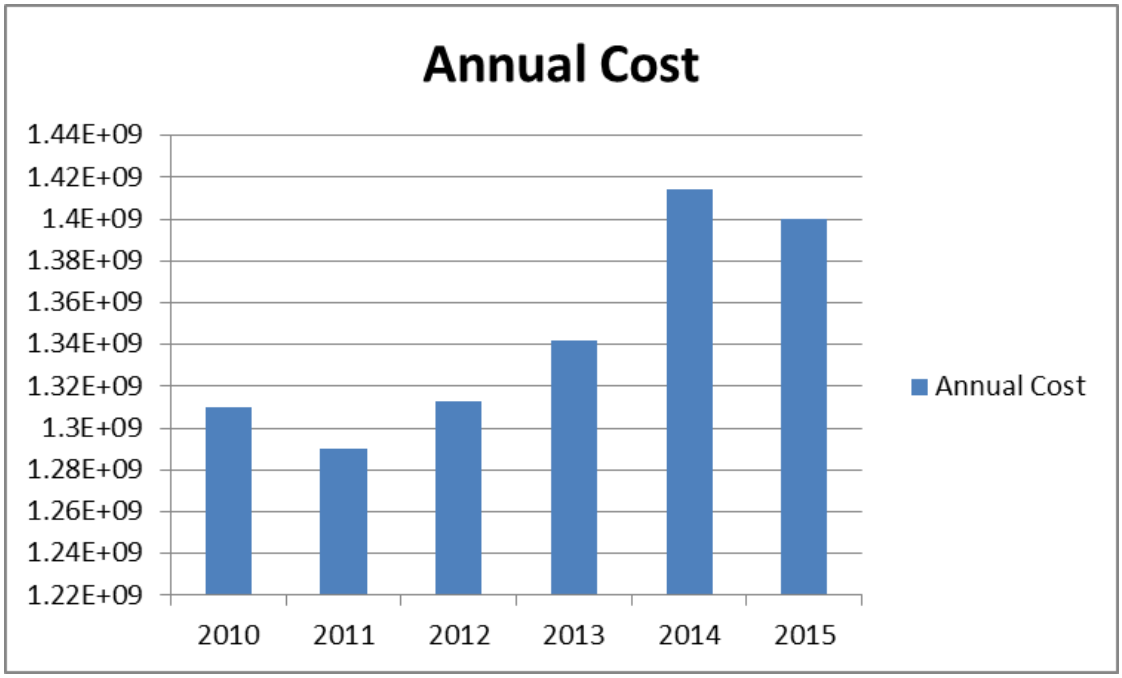


Figure 27: Annual Generation Cost

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Hourly Generation Cost	$/MWh	Yes	No	Current Cost	Decrease	Calculate	45.27	48.83	7.86%

Figure 28: Hourly Generation Cost

Increase in $/MWh is due to system wide cost instead of project cost. Project cost was impossible to calculate. The annual hourly generation cost is shown below.

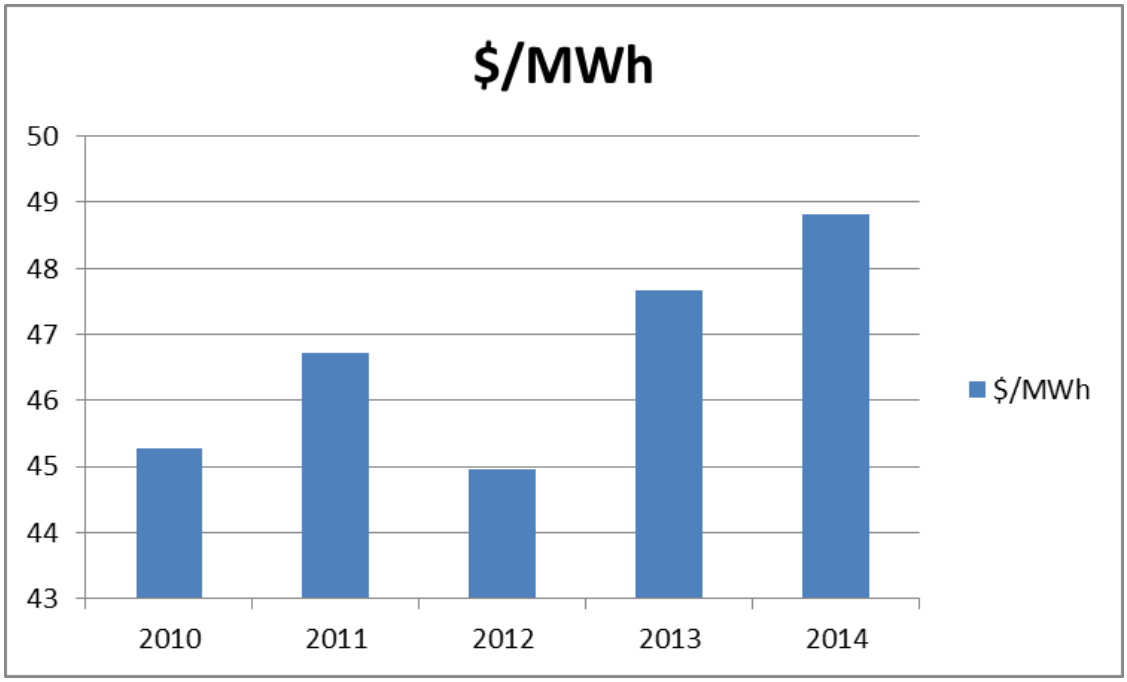


Figure 29: Hourly Generation Cost

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Annual Electricity Production	MWh	No	No	n/a	n/a	n/a	n/a	n/a	n/a
Ancillary Services Cost	$	No	No	n/a	n/a	n/a	n/a	n/a	n/a
Meter Operations Cost	$	Yes	n/a	Current Cost	Decrease	Calculate	8,515,000	8,430,000	-1.00%
Truck Rolls Avoided	#	Yes	n/a	Current Number	Decrease	Calculate	365,000	361,000	-1.10%

Figure 30: Cost Benefits

Meter Operations Cost

Baseline: $8.515 M per year system-wide. Update: $8.430 M per year system-wide

Considering LADWP's operation policy to read meters and disconnect/reconnect meters manually, most of meter operation cost remains unchanged. A small decrease of about 1% is anticipated for meter exchange cost based on the assumption that there will be less exchange of smart meters due to their better accuracy.

Electric Power Research Institute (EPRI) Cost Benefit Estimates method is used in this estimation.

Truck Rolls Avoided

Baseline: 365,000 Update: 361,000

Considering LADWP's operation policy to read meters and disconnect/reconnect meters manually, the number of truck rolls remains mostly unchanged. A small decrease of about 1% is anticipated in truck rolls due to less exchange of smart meters due to their better accuracy.

EPRI Cost Benefit Estimates method is used in this estimation.

Metrics Related Primarily to Environmental Benefits

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Meter Operations Vehicle Mile	Miles	Yes	n/a	Current miles	Decrease	Calculate	2,920,000	2,890,800	-1.00%
CO_2 Emissions	tons	Yes	Yes	Current Emissions	Decrease	Calculate	966	956	-1.04%
Pollutant Emissions (So_x, No_x, PM-2.5)	tons	Yes	Yes	Current Emissions	Decrease	Calculate	227	224	-1.32%

Figure 31: Environmental Benefits

Meter Operations Vehicle Mile

Baseline: 2,920,000 Update: 2,890,800

Considering LADWP's operation policy to read meters and disconnect/reconnect meters manually, the number of truck rolls remain mostly unchanged. Therefore, the number of driven miles remain unchanged for the most part. A small decrease of about 1% is anticipated for meter exchange cost based on the assumption that there will be less exchange of smart meters due to their better accuracy, which would reduce meter operations vehicle miles.

EPRI Cost Benefit Estimates method is used in this estimation.

CO2 Emissions

Baseline: 966 metric tons of CO2 Update: 956 metric tons of CO2

Considering LADWP's operation policy to read meters and disconnect/reconnect meters manually, the number of truck rolls remains mostly unchanged. A small decrease of about 1% is anticipated in truck rolls due to less exchange of smart meters due to their better accuracy as well as due to customers' general savings in electric energy. The anticipated reduction in truck rolls would lead to reduced CO^2 emissions.

Pollutant Emissions (Sox, Nox, PM-2.5)

Baseline: 227 metric tons Update: 224 metric tons

Considering LADWP's operation policy to read meters and disconnect/reconnect meters manually, the number of truck rolls remains mostly unchanged. A small decrease of about 1% is anticipated in truck rolls due to less exchange of smart meters due to their better accuracy and also due to customers' general

savings in electric energy. The anticipated reduction in truck rolls would lead to reduced pollutant emissions.

Estimation of GHG-other-than-CO2 based on the data that indicates CO2 accounts for about 80% of total GHG.

Metrics Related Primarily to AMI System Performance

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Meter Data Completeness	%	Yes	n/a	Zero	Increase	Calculate	0	92.61%	n/a
Meters Reporting Daily by 2AM	%	Yes	n/a	Zero	Increase	Calculate	0	85%	n/a

Figure 32: AMI System Performance

Meter Data Completeness

During the pilot, there were a number of system issues and testing activities that impacted the completeness of the meter data. The overall completeness of meter data is 88.71%. Negating reads that completed below 85%. The jobs with lower read rates (completed below 85%) were likely caused by system issues or were test job. The overall completeness of meter data is 92.61%. AMI meters enabled LADWP to retrieve meter reads remotely and accurately on a daily basis. The projected change in metric did increase from zero.

Meters Reporting Daily by 2AM

During the pilot, there were a number of system issues and testing activities that impacted the number of meters reporting by 2AM. The overall average number of meters that reported by 2AM is 45,442. Negating reads that completed under 85% (due to issues and testing), the overall average number of meters that reported by 2AM is 47,437. AMI meters enabled LADWP to remotely read meters on a daily basis. The projected change in metric did increase from zero.

Impact Metrics Storage Systems

Metrics Related Primarily to Economic Benefits

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Average Energy Storage Efficiency	%	Yes	Yes	Zero	Increase	Calculate	0	96.6 % 75.1%	n/a

Figure 33: Average Energy Storage Efficiency

In order to calculate energy storage efficiency, one charge/discharge scenario has been executed in the Garage of the Future and the energy efficiency has been calculated.

The scenario has been applied to Spare Unit to charge and discharge the battery by the grid and switching mode in every 3 hours. Battery storage is 11640Wh and it has capability to be charged and discharged from 20-95% of its capacity with maximum rate of 4.5kW.

After running this scenario the battery efficiency was 96.6% based on measuring the input output power for the period of 5-15-16 10:20 until 5-17-16 16:00. The projected change in metric did increase from zero.

Total energy in: 71440Wh.

Total Energy out: 69013Wh.

Efficiency of battery: 96.6%

For the total energy storage system the efficiency has been calculated as 75% for the same evaluation period.

Total Energy from Grid: 82802 Wh.

Total Energy to Grid: 62185 Wh.

Energy Storage efficiency: 75.1%

	Battery	Energy Storage sys.	Charging Mode	Discharging Mode
Output energy (Wh)	69013	62185	71440	62185
Input energy (Wh)	71440	82802	82802	69013
Energy Efficiency	**96.6%**	**75.1%**	**86.3%**	**90.1%**

Figure 34: Energy Efficiency

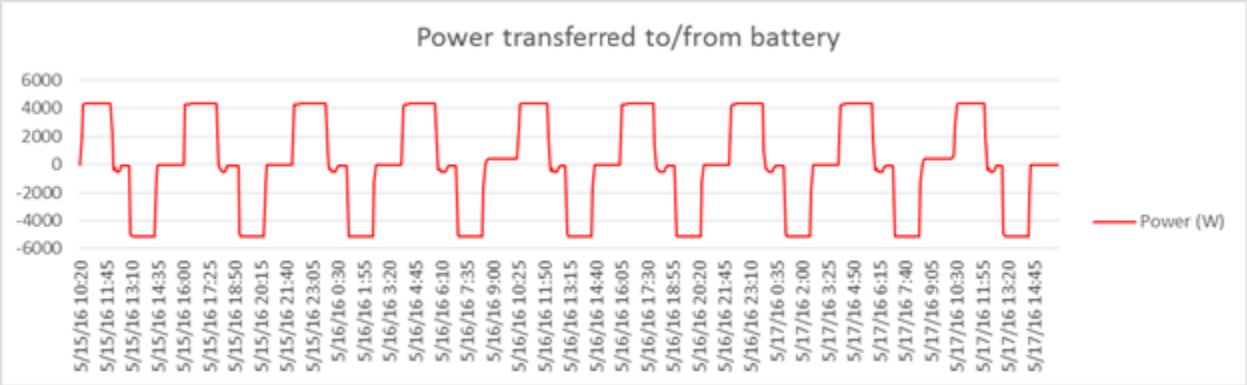


Figure 35: Power transferred to/from battery

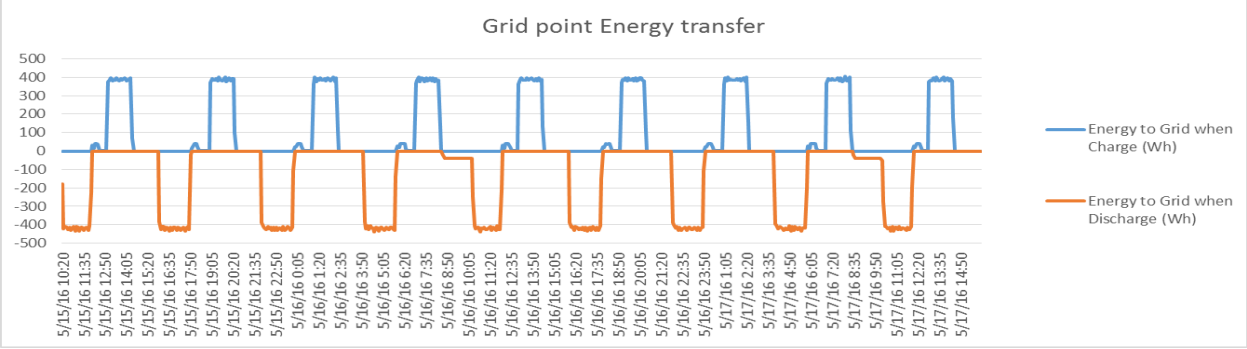


Figure 36: Grid point Energy transfer

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Annual Storage Dispatch	kWh	Yes	Yes	Zero	Increase	Calculate	0	17.46	n/a
Electric Energy Time-Shift	kWh	Yes	Yes	n/a	n/a	n/a	n/a	13.1	n/a
Electric Supply Reserve Capacity	kWh	Yes	Yes	Zero	Increase	Calculate	0	23.28	n/a

Annual Storage Dispatch

For a typical storage system as in Garage of the Future, the battery storage in each solar and wind unit is 11640Wh. Consequently, the total energy storage dispatch capability is 23.28 kWh with maximum dispatch rating of 9kW (2*4.5kW). However, due to 20-95% limitations on “State of Charge” (SOC) limits, the value is decreased to 75% which is 17.46 kWh.

Electric Energy Time-Shift

Energy Storage system at GOF can time-shift at most 17.46kWh of energy with maximum rating of 9 kW. However, due to 75% efficiency of storage system, total electric time-shift energy capacity would be 13.1 kWh.

Electric Supply Reserve Capacity

The energy storage systems at GOF can reserve a total of 23.28kWh. The projected change in metric did increase from zero.

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Voltage Support	%	Yes	Yes	Zero	Increase	Calculate	0	3.83%	n/a

Figure 37: Voltage Support

Voltage Support

In order to calculate the voltage support of energy storage system at GOF, 9kW rate of discharge (made by 2 steps of 4.5kW grid tied inverters at GOF) has been executed and the voltage increase has been measured. The energy storage system at GOF does not have the capability to inject reactive power for any purposes such as power factor correction or reactive power support or volt/VAR control. In other words, the voltage support can be provided only through active power and during the discharge of battery and feeding the energy into the grid. The average voltage increase was from 120.8 to 125.2V and consequently was a 3.83% increase. The average voltage is shown below.

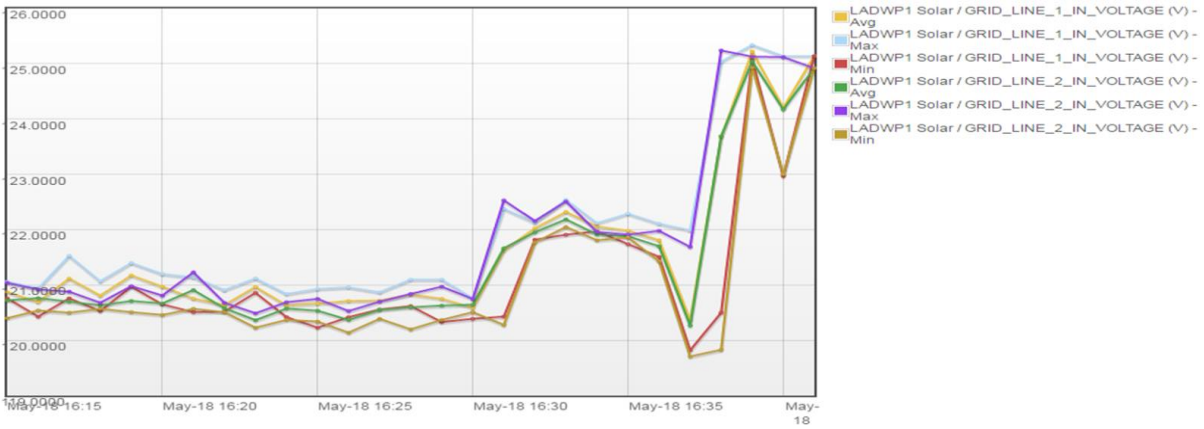


Figure 38: Average Voltage

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Monthly Demand Changes	$/kW-Month	No	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Capacity Market Value	$/MW	No	No	n/a	n/a	n/a	n/a	n/a	n/a
Ancillary Services Price	$/MWh	No	No	n/a	n/a	n/a	n/a	n/a	n/a

Figure 39: Demand

Impact Metrics Electric Distribution Systems

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Distribution Feeder or Equipment Overload Incidents	#	Yes	n/a	Current Numbe	Decrease	Count of actual number	n/a	60	n/a

Figure 40: Distribution Feeder or Equipment Overload Incidents

There is no baseline as feeder overloads were ever measured prior to the Smart Grid Demo Program.

Between the periods of 6/28/12 - 7/1/16, feeder 88-22 had 4 incidents and Feeder 88-23 had 56 incidents.

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Distribution Feeder Load	MW MVAR	Maybe	n/a	Current Load	Decrease	Calculate	n/a, See notes	n/a, See notes	n/a, See notes

Figure 41: Distribution Feeder Load

Distribution Feeder Load

Because few distribution automation installations occurred, there was little impact to the distribution feeder load. However, the installation of the six remote capacitor banks on feeders 88-22 and 88-23 were able to help alleviate the reactive power on the two feeders.

As a part of the demonstration, a capacitor bank was switched on at 8:15 PM on August 19, 2014 and then switched off at 8:45 AM on August 20, 2014. At approximately 8:15 PM on August 19, 2014, capacitor bank 2 switched on, causing the reactive power to increase. When capacitor bank 2 is switched off, the reactive power decreases.

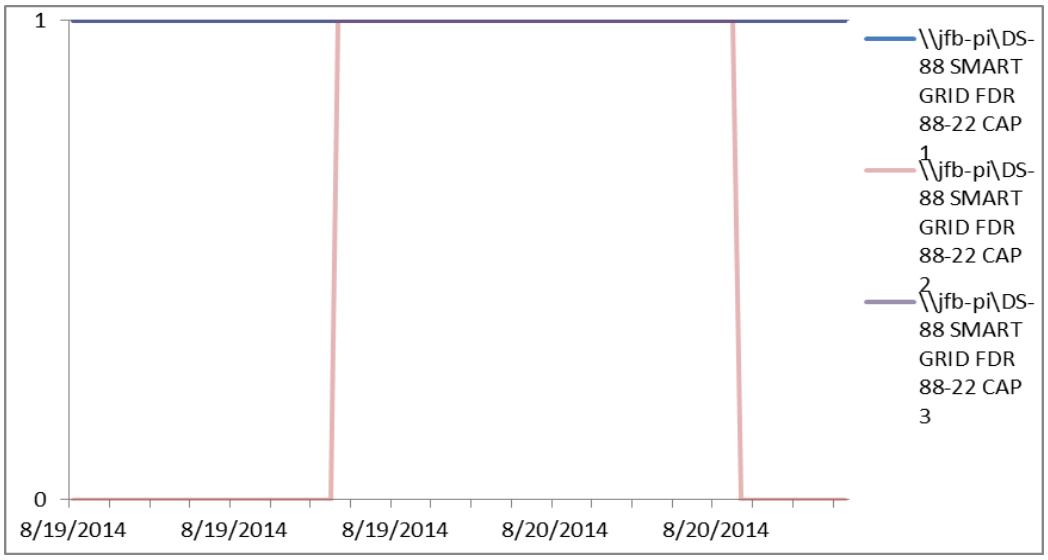


Figure 42: Capacitor Bank

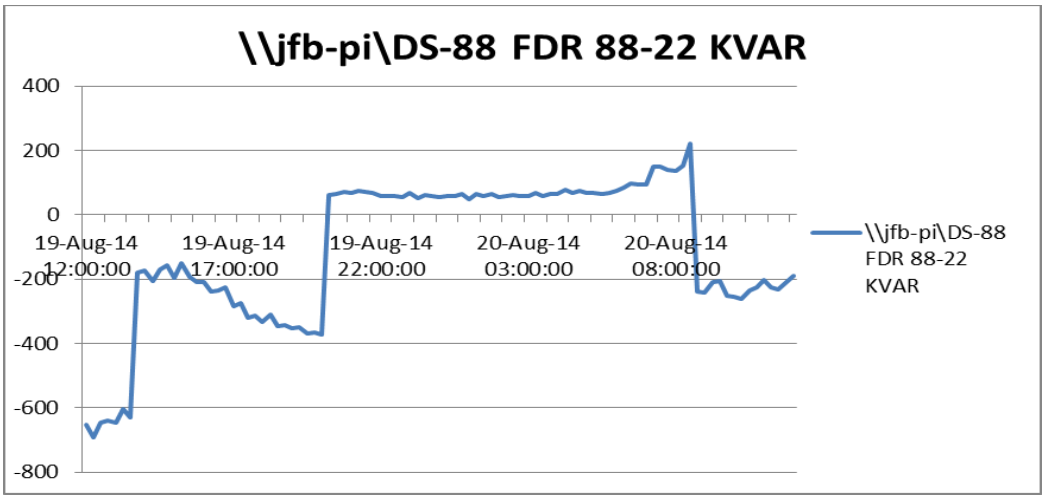


Figure 43: DS-88 KVAR

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Deferred Distribution Capacity	$	No	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Equipment Failure Incidents	#	Maybe	n/a	Current Numbe	Decrease	Count of actual	n/a	n/a	n/a
Distribution Equipment	$	Maybe	n/a	Current Cost	Decrease	Calculate	n/a	n/a	n/a
Distribution Operations Cost	$	Maybe	n/a	Current Numbe	Decrease	Count of actual	n/a	n/a	n/a
Distribution Feeder Switching	#	Yes	n/a	Current Numbe	Decrease	Count of actual	n/a	n/a	n/a
Distribution Capacitor Switching	#	Yes	n/a	Current Numbe	Decrease	Count of actual	n/a	3976	n/a
Distribution Restoration Cost	$	Yes	n/a	Current Cost	Decrease	Calculate	n/a	n/a	n/a
Distribution Losses	%	No	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Distribution Power Factor	pf	Maybe	n/a	Current Power Factor	Decrease	Calculate	n/a	n/a	n/a
Truck Rolls Avoided	#	Maybe	n/a	Current Truck Rolls	Decrease	Count of actual Truck Rolls	n/a	n/a	n/a

Figure 44: Electric Distribution Systems

Distribution Capacitor Switching Operations

No baseline was ever established because there was no way of determining when a capacitor bank switched before the controller was installed.

From July 1, 2014 to June 21, 2016, 3,925 Capacitor Bank switches occurred with 51 operator control switching.

Distribution Restoration Cost

Distribution Restoration Cost at a project level was not tracked as a subset of the total population, so data was not available to compare.

Distribution Power Factor

As seen in the Distribution Feeder Load section, when the capacitor bank switches, the power factor improves.

Metrics Related Primarily to Reliability Benefits

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
SAIFI	Index	Yes	n/a	Current Index	Decrease	Calculate	1.03	0.70	-32.04%
SAIDI/CAIDI	Index	Yes	n/a	Current Index	Decrease	Calculate	214.44	85.34	-60.20%
MAIFI	Index	Yes	n/a	Current Index	Decrease	Calculate	0.296	0.383	29.39%
Outage Response Time	Minutes	Yes	n/a	Current Response Time	Decrease	Calculate	2,058 hours total time of customers outage	1,857 hours total time of customers outage	-9.77%
Major Event Information	Event Statistics	Yes	n/a	Current Statistics	Decrease	Describe and calculate	1,493,405 customers experienced loss of service due to major	2,495,790 customers experienced loss of service due to major	67.12%
Number of High Impedance Faults Cleared	#	No	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Figure 45: Reliability Benefits

SAIFI

Two reports have been used for this information: http://prp.ladwp.com/ and http://opa.lacity.org/documents/costreductionreport20120823.pdf (page 37). Decrease of SAIFI is result of a combination of various factors, not only implementation of Smart Grid technology.

SAIDI/CAIDI

Two reports have been used for this information: http://prp.ladwp.com/ and http://opa.lacity.org/documents/costreductionreport20120823.pdf (page 37). Decrease of SAIDI is the result of a combination of various factors, not only implementation of Smart Grid technology.

MAIFI

MAIFI is calculated based on the data of outage reports on DWP's Trouble Center website. It has increased instead of decreased.

Outage Response Time

Information obtained from LADWP Electronic Trouble System. Considering partial deployment of Smart Grid, it has not had much effect on restoring such outages. Outage signals from deployed smart meters, however, have successfully been used in the OMS system during 2015 and 2016 to confirm group outages before receiving the calls.

Major Event Information

Information obtained from LADWP Electronic Trouble System. Considering partial deployment of Smart Grid, it has not had much effect on restoring such outages. Outage signals from deployed smart meters, however, have successfully been used in the OMS system during 2015 and 2016. The projected change was decrease, but the effect was an increase in event statistics.

Metrics Related Primarily to Environmental Benefits

Metrics	Value	Project Level	System Level	Build Indicator (Metrics) Baseline Measure	Projected Changes in the Metric from Baseline	Build Measurement Technique	Baseline	Update	Variance
Distribution Operations Vehicle	Miles	No	n/a	n/a	n/a	n/a	n/a	n/a	n/a
CO_2 Emissions	tons	No	No	n/a	n/a	n/a	n/a	n/a	n/a
Pollutant Emissions (So_x, No_x, PM-2.5)	tons	No	No	n/a	n/a	n/a	n/a	n/a	n/a

Figure 46: Environmental Benefits

The following table shows the impacts and benefits of each project throughout the duration of the Program:

Benefit Type	Categories	AMI	CB	CS	DR	EV
Energy and Cost Savings	Utility Bill Savings	X			X	X
	Peak Demand Reductions				X	X
	Energy Savings	X			X	X
	Reduced Utility Capital Expenditures	X		X	X	X
	Reduced Utility Maintenance Expenditures	X		X	X	
	Avoided Procurement Costs	X	X	X	X	X
Greater Reliability	Reduced Frequency of Service Interruptions	X			X	X
	Reduced Duration of Service Interruptions	X			X	X

	Improvement in Power Quality				X	X
Addressing Barriers	Grid Integration	X		X	X	X
Information Dissemination	Journal Articles Published		X	X	X	X
	Web-based surveys of people viewing materials or participating in program reviews		X			
Adoption of technology, strategy, and research data/results by others	Availability of a new technology for sale in the marketplace	X			X	X
	Customers using web portal to identify and modify usage behavior		X			
Economic Development	Job Creation	X	X	X	X	X
	Economic Growth	X	X	X	X	X
Environmental Benefits	GHG Emission Reduction				X	X

Table 37: Impacts and Benefit

6 Demonstration Project Areas

Customer Behavior Project

Demonstration	Demonstration Description	Functions To Be Demonstrated	Tangible Deliverable
Customer Behavior Studies using the USC campus test bed	The USC campus test bed will provide to the Demonstration a unique combination of facility types (offices, hospitals, residences, laboratories, and retail), integrated energy services operations, multi-disciplinary research capabilities, and an exceptionally diverse community of faculty, students, and staff. The lessons learned and best practices developed from Customer Behavior studies conducted within the test bed (USC campus and surrounding neighborhoods) will be utilized to support and optimize LADWP's large-scale Smart Grid deployment.	1. The impact of smart grid communication systems and processes on customer usage patterns. 2. Effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns. 3. The introduction and trial of new energy-related information and interface technologies to energy use data and information. 4. Communication and media content on Smart Grid deployment, incorporating changes observed in awareness, attitudes, and energy use behaviors. 5. Multi-level educational products targeted to learning about Smart Grid technologies and their implementation. 6. Energy savings resulting from the use of smart grid-enabled interfaces, pricing options, and programs.	1. Identification of the effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns. 2. Identification of the key socio-demographic and community structure variables in the Smart Grid adoption process. 3. Identification of the key decision factors in the adoption of Smart Grid-related technologies. 4. Integration of behavioral and social factors into the design and implementation of Smart Grid information architecture, data management, and cyber-security systems. 5. Deliver comprehensive data, analysis, and models relating to socio-demographic compositions and customer use types to Smart Grid technology

			acceptance and use patterns. 6. Develop and test applications for a broad array of customer interfaces to energy information including an understanding of the impacts of emerging social media (Facebook, Twitter, etc.) 7. Periodic reports documenting the results of the demonstration. 8. Final specifications and reports – 12/2015.
Measure and track, against the baseline, attitudes and behaviors relevant to EVs and the potential to buy in the future.	Conduct a survey at the household level for a random set of customers in the LADWP service area concerning what cars they own and what cars they may buy in the future.	1. Demonstrate differences and similarities in attitudes, values, and beliefs (between distinct target audiences) that predict intent to purchase Electric Vehicles, compared to traditionally powered alternatives. 2. Demo effective messaging strategies to educate different/distinct target customer types/groups about factors which predict purchase and usage of Electric Vehicles (instead of traditionally powered vehicles).	1. Enhanced customer communication materials (e.g., newsletter, website) to increase awareness and understanding of increasing availability of electric vehicles. 2. Periodic reports documenting the results of the demonstration 3. Final specifications and reports – 12/2015
Customer Communications and Education	LADWP will be able to use the outcomes from within the test bed and from surveys developed for the LADWP customer base as input to making changes to the communications and outreach plan for LADWP's 4	1. Differences and similarities between different target audiences by demographic, psychographic features, as well as by consumer type (e.g., household, commercial, retail).	1. Enhanced customer bill to teach energy literacy and encourage energy efficiency. 2. Enhanced customer website to educate customers about the Smart Grid and energy

	million customers, including: Changes to the CIS (Customer Information System), IVR (Interactive Voice Response) system, Web Portal redesign, Bill Redesign and Bill Print upgrade	2. Demographic and psychographic factors that predict customers' (or end users') affective and behavioral responses to Smart Grid, Smart Meters, and related technologies. 3. Effective messaging strategies to educate different/distinct target customer types/groups. 4. Features and benefits (of Smart Grid, Smart Meters, and related technologies) that promote/predict increased acceptance and adoption, and those that promote/predict increased customer satisfaction. 5. Effective strategies for utilizing the influence of opinion leaders. 6. Effective target marketing (of Smart Grid, Smart Meters, and related technologies) to increase customer adoption via website, newsletter, billing, and other communications. 7. Demo community outreach and education programs.	efficiency. 3. Public outreach and educational forums (e.g., energy and behavior conference, forums, etc.). 4. Integration of energy literacy curriculum into existing or new courses. 5. Periodic reports documenting the results of the demonstration. 6. Final specifications and reports – 12/2015

Table 38: Customer Behavior Demonstrations

Demand Response / Advanced Metering Infrastructure Project

Demonstration	Demonstration Description	Functions To Be Demonstrated	Tangible Deliverable
AMI communications and Smart Meter deployment (UC8)	While LADWP is already committed to installing AMI communications infrastructure and Smart Meters, the demonstration will test the viability of several Smart Meter technologies to meet customer and LADWP requirements. This will provide cost effective input to choose the best technology in deploying Smart Meters to all LADWP customers.	1. Demonstrate the initiation of a meter the first time it's installed 2. Demo the benefits of potential "automatic demand response" through AMI versus manual demand response 3. Demo how AMI supports customer rates/pricing options 4. Demo how AMI and data integration with LADWP systems facilitates a Distribution Management System (DMS) and Outage Management System (OMS)	1. Periodic reports documenting the results of the demonstration 2. Final specifications and reports 12/2015 3. Modeling and analysis for demand periods: Hourly, daily, seasonal, annual 4. Analysis of: shifting/shedding and grid reliability 5. Integration of customer surveys/market test data to help determine rate options/pricing incentives for full-scale AMI implementation 6. Integration of AMI and AMI meter data with other LADWP systems for DMS and OMS functionality
Demonstrate Demand Response events in LADWP's Smart Grid Demo Lab Control Center	The Control Center demonstration in the SG Demo Lab will provide (Los Angeles Department of Water and Power) LADWP with a real time perspective of the impact on the LADWP system when the campus test beds' micro grids respond to an LADWP initiated demand response event.	1. Demonstrate successful two-way communication with smart meters. 2. Demo control over voltage adjustment where it's needed to manage the demand. 3. Demo two way communications with smart appliances. 4. Demo customer interface, including updated DWP website to	1. Periodic reports documenting the results of the demonstration 2. Final specifications and reports 12/2015 3. Successful two-way communication with smart meters. 4. Control over voltage adjustment where it's needed to manage the demand. 5. Two-way

		monitor and control demand. 5. Demo tools for data and power flow to correct the distribution system 6. Demo the impact of distributed generation, storage, and new demand technologies (as they become available) on building, sub-system, and grid level performance. 7. Demonstrate the power quality impacts of building-to-grid load management systems and optimization on "digitally-dependent" customer applications associated with high-performance computing, laboratory, and medical sub-systems.	communication with smart appliances. 6. Customer interface to monitor and control their demand. 7. Update DWP website with new capabilities for interface. 8. Develop tools for data and power flow to correct distribution system 9. Test and validate the impact of distributed generation, storage, and new demand technologies (as they become available) on building, sub-system, and grid level performance. 10. Determine the power quality impacts of building-to-grid load management systems and optimization on "digitally-dependent" customer applications associated with high-performance computing, laboratory, and medical sub-systems.
Large commercial customer participating in DR program: USC Campus Demonstrating B2G	While this technology holds immense promise for building managers and utilities alike, much is untested. Connecting Building Automation Systems, and on-site renewables/other generation and storage devices to the grid, LADWP	1. Demonstrate successful building-to-grid system integration 2. Demo integrated system optimization scenarios across the diverse building portfolio of the campus test bed including: loading and	1. Periodic reports documenting the results of the demonstration 2. Final specifications and reports 12/2015 3. Comprehensive suite of case studies on building-to-grid

Technologies (UC5)	will use this information for grid optimization, market-based pricing, and improvements in efficiency, reliability, and power quality for commercial and industrial customers.	demand management interactions for building sub-spaces and infrastructure sub-systems (water, heating / cooling, etc.). 3. Demo the impact of measurement density (energy use, temperature, etc.) on system performance and optimization. 4. Demo the power quality impacts of building-to-grid load management systems and optimization on "digitally-dependent" customer applications associated with high-performance computing, laboratory, and medical sub-systems. 5. Demo the impact of distributed generation, storage, and new demand technologies (as they become available) on building, sub-system, and grid level performance. (UC5)	integration demonstrations including identified processes, barriers, and best practices. Studies will have evaluated the impact of building, infrastructure sub-system, and grid control and optimization technologies across a range of customer use environments (residential, commercial, etc.). 4. Deliver an integrated set of energy measurements including efficiency, power quality, and environmental performance (incorporating the USC Green House Gas (GHG) emissions management system).
Communications protocol and prototype Home Area Network (HAN) using WINSmartGrid Technology (UC3)	Home Area Networks (HANs) will connect appliances, on-site renewables, and storage devices in homes to the grid for access to real-time energy usage and pricing information, and providing the ability to react to demand response events from LADWP. An open, standards-based, and flexible	1. Demonstrate capabilities and interoperability of different automation sensing, monitoring, and control technologies 2. Demo wired and wireless networking and communication technologies for HAN 3. Demo how the integrated automation	1. Periodic reports documenting the results of the demonstration 2. Final system specifications and reports - 12/2015 3. Evaluation of technical capabilities and interoperability of different automation sensing, monitoring and

	architecture for HANs is important to ensure longer life as the technology evolves. This demonstration involves protocols and prototypes for communications, and sense-and-control and information-based systems for HAN using UCLA WINSmartGrid technology.	network and AMI infrastructure support energy usage models, pricing models and demand-response events and messaging	control technologies 4. Evaluation of wired and wireless networking and communication technologies for HAN/BAN, NAN and WAN 5. Aggregate technology and system features and capabilities to assist open system development using UCLA-WINSmartGrid technology 6. Integration of automation network with AMI infrastructure, energy usage models, pricing models and demand-response events and messaging to support LADWP's service domain.
Demand Response Optimization Using Service-Based Software architecture. (UC6)	The USC facilities which include a full range of user infrastructures: Commercial, medical, retail, semi-industrial, and residential will be used for this demonstration. This will provide LADWP with outcomes and performance data for deploying fully-integrated DR Smart Grid operations and technologies for all customer types. The demonstration outcomes and data can then be used by LADWP for full scale deployment; for developing the business case and for	1. Demonstrate a full campus-wide integrated Smart Grid infrastructure incorporating both existing and new energy and information systems. 2. Demo targeted load curtailment, using different types of load profiles and customer service requirements, different facility configurations, and different network technologies and strategies. 3. Demo demand response events and processes, highlighting seamless	1. Periodic reports documenting the results of the demonstration 2. Final system specifications and reports - 12/2015 3. Development and execution of test plans to demo targeted load curtailment, different types of load profiles and customer service requirements, different facility configurations, and different network technologies and strategies. 4. Design, development,

	selecting the best operational models and technologies.	operation of services-based architecture, granularity of load control, cyber security controls, and compliance with customer's load profiles and service requirements. (UC6)	and implementation of an advanced Smart Grid architecture, integrating operations, control, data management systems, and cyber-security. 5. Testing and validation of operational and demand response configurations and scenarios and detailed performance data and analysis to support LADWP full deployment objectives. 6. Integration of Customer Behavior research and demonstration programs, including incorporation of customer information and data access technologies. 7. Establish and manage internal and external community communications processes regarding the demonstration. 8. Establish and manage technology selection & testing programs for Smart Grid technology vendors.
Large Commercial, Industrial and Institutional Customers	LADWP offers a DR program to selected large customers who have indicated an ability and willingness to provide load curtailment during a DR	1. Educate customers about how they currently use energy and how their current energy use patterns impact their electricity	1. Periodic reports documenting the results of the demonstration 2. Customer energy usage specifications and

participating in DR Program: LADWP Demonstration (UC4)	request. This is a volunteer group which will be used to test the initial program design prior to rollout to a larger subset of customers. In order to participate in the LADWP DR program to be offered during the demonstration, large commercial customers will implement at least some of the steps in the B2G scenario, depending on applicable energy end-uses and technologies in their buildings and come up with a verified DR curtailment based on LADWP announcements.	costs through participating in DR program 2. Provide customers with information from energy assessment tools to clearly understand how to achieve additional cost reductions through a time-based rate, or dedicated rates 3. Persuade customers to move to a time-based rate or participate in pilot DR Programs. 5. Obtain customer input regarding preferred features for DR programs 6. Test DR Automation technologies for commercial buildings. 7. Conduct education sessions with small commercial customers regarding DR automation and control systems 8. Demonstrate how DR automation makes it easy for customers to respond to a load curtailment event, and to understand how customer control and choice in the response motivates customers to opt in.	reports - 12/2015 3. Development and execution of energy audit plans for Commercial, industrial and Institutional customers, with different types of load profiles and customer service requirements, different facility configurations, and different BAS technologies and strategies. 4. Testing and validation of operational and demand response configurations and scenarios and detailed performance data and analysis wen visiting customers to support LADWP full deployment objectives. 5. Establish and manage internal and external community communications processes regarding the DR events and demonstration. 8. Establish and manage DR energy audit and customer outreach program templates for CII customers.

Table 39: DR Demonstrations

Electric Vehicles Project

Demonstration	Demonstration Description	Functions To Be Demonstrated	Tangible Deliverable
Smart charging using WINSmartGrid for EV and existing charging stations and EV's in and around Los Angeles and the UCLA campus	The demonstration of automated smart charging using wireless communications will take into account cyber security concerns, reliability, and result in outcomes to help determine upgrades required to the LADWP electric distribution system (transformers/wires) with full scale implementation of EVs.	1. Demo monitoring of all Chargers. 2. Demo reading of power consumption for the vehicles. 3. Demo control of the chargers (time/usage). 4. Demo disconnect of the chargers. 5. Demo smart charging through mobile interfaces.	Report on smart charging infrastructure results (Data and Controls). Completed by 12/2015
Battery aggregation and backfill	Determine how to locally aggregate EV batteries to serve as backfill into the LADWP power grid. This provides local grid stability, and by ensuring that sub-sections of the grid maintain an available back-up power supply, can serve as a primary prevention against large-scale outages. Backfilling can also provide an effective means of load leveling power supply for customers in the event of a power outage to reduce LADWP costs and improve customer reliability and satisfaction.	1. Demo use of the batteries into the grid (1 way - charging only). 2. Demo use of the batteries into the grid (2 way - charging and discharge). 3. Demo distribution effects.	Report on integration and aggregation of EV batteries into the power grid Completed by 12/2015
Fully operational microgrid. The scalability of the wireless, sensing, monitoring and control within the WINSmartGrid	Other demonstrations that have been performed in the EV Project will be included in this fully integrated demonstration. A key outcome for use by LADWP will be the demonstrated ability of the Microgrid to operate either off-grid or on-grid and the viability	1. Demo inductive charging (remote charge, no wires). 2. Demo various vehicles charging. 3, Demo distribution effects. 4. Demo local grid balancing management.	Report on EV charger integration and the impact on the grid Completed by 12/2015

EV framework will be studied during the research. Scalability will be studied in the context of the UCLA Microgrid.	of the fully automated wireless sensing, monitoring and control to move between these two states depending on system conditions.		
Renewables and battery integration	Demonstrate the viability of using charged EV batteries as an integrated set of storage devices to use for maintaining grid integrity as LADWP pursues its RPS and related IRP goals	1. Demo use of community storage on EV batteries and external storage. 2. Demo garage of the future. 3. Demo cycling of the batteries. 4. Demo aggregation of the batteries. 5. Demo integrated EV and solar.	Report on the usage of EVs as renewables Completed by 12/2015
Using car sharing programs at USC and UCLA	This provides the opportunity to use two distinct test-beds that include different user demographics, grid specifications, and driving patterns. UCLA and USC are in different areas of Los Angeles that result in different average distances traveled per car trip, a key factor in planning the rate and capacity of charge provided to a fleet of EVs. This information can be used by LADWP for full scale Smart Grid implementation planning.	1. Demo monitoring of chargers, power usage, and car usage. 2. Demo distribution effects	Report on EV usage, consumption, and charging Completed by 12/2015
Grid Impact Stability/Power Study	Demonstrate the impact of EVs on the Electrical Grid	1. Demo generation, transmission, & distribution effects. 2. Demo various loading scenarios.	Report demonstrating the impact of EVs to the grid Completed by 12/2015

Table 40: EV Demonstrations

Cyber Security Project

Demonstration	Demonstration Description	Functions To Be Demonstrated	Tangible Deliverable
Grid resilience against cyber attacks	This is a demonstration of the Grid's active defenses against cyber-attacks. It will take into account the accuracy and timeliness of detection and response and the outcome will lay out the pros and cons that accompany the full-scale deployment of such active cyber defense.	1. Demonstrate the capability to detect attacks. 2. Demonstrate the capability to diagnose the provenance of attacks. 3. Demonstrate the capability to remediate or contain the consequences of cyber-attacks.	1. Periodic reports documenting the results of the demonstration 2. Final reports – 12/2015
System Integrity	This is a demonstration of the ability of the Smart Grid to detect and recover from compromises of system integrity, including software and firmware modifications (possibly resulting from malware attacks), and the addition of unauthorized physical components to the system.	1. Demonstrate the detection of manual inserted changes to software on all classes of nodes. 2. Demonstrate the reconfiguration and/or recovery to legitimate software configuration on affected components.	1. Periodic reports documenting the results of the demonstration 2. Final reports – 12/2015
Secure Data Management	A demonstration of the ability of the Smart Grid infrastructure to limit the flow of customer, configuration, and audit data according to defined policies and to protect the integrity of the data.	1. Demonstrate the detection of modified billing, configuration and audit data, and behavior of system upon detection. 2. Demonstrate the denial of attempts to access or transmit data where such access or transmission is counter to defined information flow policies.	1. Periodic reports documenting the results of the demonstration 2. Final reports – 12/2015

Testing: Effectiveness	A demonstration, through emulation on the Defense Technology Experimental Research (DETER) cyber-security test bed, the effectiveness of the security measures within the Smart Grid architecture.	1. Demonstrate the systemic response to various threats such as malware penetration and physical threats that will affect parts of the Smart Grid.	1. The design of the security mechanisms for the Smart Grid demonstration project – this is a prerequisite to the deployed system, and to this demonstration 2. The model/architecture of the cyber-security infrastructure for the Smart Grid. 3. Periodic reports documenting the results of the demonstration 4. Final specifications and reports – 12/2015
Testing: Predictive capability	A demonstration of the effectiveness of the proposed security capabilities when extended to a full-scale implementation of the Grid.	1. Demonstrate the issues (limitations and possibilities) facing a full-scale deployment of the cyber-security approach.	1. The architecture of the cyber security infrastructure for the Smart Grid demonstration project – this is a prerequisite to the deployed system, and to this demonstration 2. The model/architecture of the cyber-security infrastructure for the Smart Grid. 3. Periodic reports documenting the results of the demonstration 4. Final specifications and reports – 12/2015

Table 41: CS Demonstrations

The tables below present a complete listing of the Use Cases from each of the SGRDP projects:

Use Case/ Scenario ID	Use Case Name
Use Case AMI-1	Use Case AMI-1.000 Install Head-End
Use Case AMI-2	Use Case AMI-2.000 Design Communication Network & Select Site
Use Case AMI-3	Use Case AMI-3.000 Design Back Haul Communication Network
Use Case AMI-4	Use Case AMI-4.000 Construction / Site Preparation for Communication Devices
Use Case AMI-5	Use Case AMI-5.000 Install Communication Device
Use Case AMI-6	Use Case AMI-6.001 Install AMI Meter (Power/PQ/Water Meter)
Use Case AMI-7	Use Case AMI-7.001 Perform Communication Network Tuning
Use Case AMI-8	Use Case AMI-8.001 Operate AMI System

Table 42: AMI Use Cases

Use Case ID:	Use Case/ Scenario Name
Use Case DR-1	**Integration of Historical and Real-time AMI and System Data for Making Outage and Demand-Side LM Decisions**
Use Case DR-1 Scenario 1	DR-1 Scenario 1: System Operator Integrates Data to Facilitate Outage Management System
Use Case DR-1 Scenario 2	DR-1 Scenario 2: ECC Operator Demonstrates Control of Voltage Adjustment to Manage Load Demand, and Integrates AMI Data to Verify Energy Savings
Use Case DR-1 Scenario 3	DR-1 Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side LM

Use Case ID:	Use Case/ Scenario Name
Use Case DR-CB2	**Residential Customer manages energy use using the LADWP Web Portal**
Use Case DR-CB2 Scenario 1	DR-CB2 Scenario 1: Home Energy Information (HEI) service (Version 1 – Home Energy Profile)
Use Case DR-CB2 Scenario 2	DR-CB2 Scenario 2: Enhanced Home Energy Information (HEI) service
Use Case DR-CB3	**Residential Customer participates in HEM and DR Programs**
Use Case DR-CB3 Scenario 1	DR-CB3 Scenario 1: Customer participates in HEM test program
Use Case DR-CB3 Scenario 2	DR-CB3 Scenario 2: Customer with HAN participates in DR demonstration program
Use Case DR-CB3 Scenario 3	DR-CB3 Scenario 3: Customer without HAN participates in DR demonstration program
Use Case DR-CB4	**Small Commercial Customer participates in Commercial Energy Information (CEI) and DR Program**
Use Case DR-CB4 Scenario 1	DR-CB4 Scenario 1: Small Commercial Customer participates in CEI Program
Use Case DR-CB4 Scenario 2	DR-CB4 Scenario 2: Small Commercial Customer with building control system participates in DR Program
Use Case DR-CB5	**Large Commercial Customers Participate in DR Program**
Use Case DR-CB5 Scenario 1	DR-CB5 Scenario 1: Large commercial customers implements building-to-grid (B2G) technologies
Use Case DR-CB5 Scenario 2	DR-CB5 Scenario 2: Large Commercial Customer participates in DR Program
Use Case DR-6	**DR Optimization in Campus Test Bed Micro-Grid Using Service-Based Software Architecture**
Use Case DR-6 Scenario 1	DR-6 Scenario 1: Reliable and precise responses to utility DR curtailment events
Use Case DR-6 Scenario 2	Use Case DR-6 Scenario 2: Load demand forecast and curtailment strategy selection using DR software architecture
Use Case CB-7	**USC Micro-Grid building occupants participate in DR events via voluntary curtailment**

Use Case CB-7 Scenario 1	CB-7 Scenario 1: Building occupants participate in Micro-Grid response to a DR event (pre-event, during event, after event)
Use Case DR-8	**Integration of AMI Data for Coordinated Voltage and Reactive Power (Volt/VAR) Optimization and Control in Improving Distribution System Performance**
Use Case DR-8 Scenario 1	DR-8 Scenario 1: Coordinated Volt/VAR control

Use Case ID:	Use Case/ Scenario Name
Use Case CB-9	**LADWP-wide Initial Baseline survey**
Use Case CB-9 Scenario 1	CB-9 Scenario 1: LADWP customers complete a baseline survey on behavior, attitudes, opinions, etc related to energy use, smart meters, and related technology
Use Case CB-10	**LADWP-wide Final follow-up survey**
Use Case DR-10 Scenario 1	DR-10 Scenario 1: LADWP customers complete a follow-up survey on behavior, attitudes, opinions, etc related to energy use, smart meters, and related technology to assess how these constructs changed over the project lifetime. Enhanced recruitment efforts among SGRDP participants to obtain feedback on project.

Table 43: CB and DR Use Cases

Use Case/ Scenario ID	Use Case Name
Routine Operations Scenarios	
AMI-CS-1	Meter Reading Services
AMI-CS-2	Revenue Protection
AMI-CS-3	Remote Connect/Disconnect
AMI-CS-4	Outage Detection
AMI-CS-5	Meter Maintenance
AMI-CS-6	Meter Removal Detection
AMI-CS-7	Meter Bypass Detection
DR-CS-1	Time Of Use Pricing
DR-CS-2	Net Metering
DR-CS-3	Feed-In-Tariff Pricing
DR-CS-4	DR Request
EV-CS-1	Customer Connects EV
EV-CS-2	PHEV or Customer Participates in DR Events
EV-CS-3	PHEV or Customer Responds to Utility Pricing Signals
EV-CS-4	Mobile Plug-In EV Functions
CB-CS-1	Customer Tracks Energy Usage
CB-CS-2	Customers Participate in On-Line Reviews / Surveys
CO-CS-1	AMI Meter Reading Service
CO-CS-2	PHEV or Customer Participates in DR Events
NOM-CS-1	Operator monitors system security status.

Table 44: CS Use Cases

Security Event Response Scenarios – Detection, Diagnosis, Response	
DDR-CS-1	Detection of security event with no response
DDR-CS-2	Detection of security event with automated response
DDR-CS-3	Detection of security event with operator-in-the-loop response
DDR-CS-4	Restoration of routine operations following a security event
DDR-CS-5	Failure of CS component – detection and response
Maintenance Scenarios – Risk Assessment and Security Updates	
MNT-CS-1	Risk Assessment updates
MNT-CS-2	Modification or implementation of monitor
MNT-CS-3	Modification or implementation of detector
MNT-CS-4	Modification or implementation of diagnosis engine
MNT-CS-5	Modification or implementation of response
MNT-CS-6	Modification or implementation of policy
MNT-CS-7	Creation or modification of identity and respective authority

Use Case/ Scenario ID	Use Case Name
Smart Charging	
Use Case EV1	Monitoring of All Chargers
Use Case EV2	Reading Power Consumption for Vehicles connected to Chargers
Use Case EV3	Control of Chargers
Use Case EV4	Disconnect Vehicle that is Charging
Use Case EV5	Smart Charging thru Mobile Interface
Battery Aggregation and Backfill	
Use Case EV-6	Use of Batteries in Grid (G2V)
Use Case EV-7	Use of Batteries in Grid (G2V & V2G)
Use Case EV-8a	Distribution Effects of Battery Aggregation and Backfill (G2B)
Use Case EV-8b	Distribution Effects of Battery Aggregation and Backfill (B2V)
Use Case EV-8c	Distribution Effects of Battery Aggregation and Backfill (B2G)

Use Case/ Scenario ID	Use Case Name
Fully Functional Microgrid	
Use Case EV-9	Inductive Charging
Use Case EV-10	Various Vehicle Charging
Use Case EV-11	Distribution Effects of EV's on the Grid
Use Case EV-12	Local Grid Balancing and Management
Renewables and Battery Integration	
Use Case EV-13	Community Storage of EV Batteries and External Storage
Use Case EV-14	Garage of the Future
Use Case EV-15	Cycling of the Batteries
Use Case EV-16	Aggregation of the Batteries
Use Case EV-17	Integration of EV and Solar
Car/Ride Share Program	
Use Case EV-18	Monitoring of Chargers, Power Usage, and Car Usage
Use Case EV-19	Distribution Effects of Car / Ride Share Program
Use Case EVGrid Impact	
Use Case EV-20a	Generation, Transmission, and Distribution Effects
Use Case EV-20b	Generation, Transmission, and Distribution Effects
Use Case EV-21	Various Loading Scenarios
Use Case EV Adoption	
Use Case EV-CB1	Baseline survey of attitudes about EV adoption

Table 45: EV Use Cases

7 Customer Behavior Overview

7.1 Summary

The overall goal of the Customer Behavior (CB) Project demonstrated the impact of the adoption, use, and penetration of Smart Grid and home automation integrated technologies on customer awareness, attitudes, and behaviors related to energy use and management.

New developments in Information Technology on both the customer and utility sides of the meter, such as an AMI and HEM systems, and Smart Grid applications offer the potential for the sophisticated integration of demand-side resources into utility operations to support improved grid reliability and cost containment. For this potential to be realized, utility customers will need to be better informed, motivated, and able to manage their energy use and participate in DR.

The CB demonstrations seek to prove that targeted messaging directed to specific segments of the population at the appropriate time and in the appropriate format, will produce positive customer reaction.

The CB demonstrations seek to keep residential utility customers better informed and responsible for their power consumption through the use of web and smart device enabled applications, billing, and other multi-media. Another CB objective was to provide data on how grid consumption patterns would change when consumers have increased ability to monitor their energy and make informed decisions about usage.

Below is a list of key deliverables for CB project:

1. Report on number of and type of inquiries/requests processed by the Smart Grid Los Angeles Call Center (LADWP Internal Report)

2. Outreach Videos 1-6

3. EV Survey Instrument: Survey in MS Word Format that assessed
    - EV adoption rates and correlates of adoption
    - Attitudes towards, perceptions of, and willingness to adopt EV's

4. EV survey outreach/recruitment: Recruitment letter/postcard to encourage survey completion and return. As part of the letter, a persuasive messaging experiment will test the influence of various messages on survey return rates and willingness to adopt EV's.

5. EV Survey Databases: Data from returned EV survey entered into Microsoft Excel Database

6. EV Survey Reports
    - Report in MS word format summarizing key results from EV survey, including:
        - Customer perceptions, attitudes, and willingness to adopt EV's.
        - Influence of persuasive messages on results

7. CB9 Customer Baseline Survey. Survey in MS Word Format that assessed the following:

- CB goals/ objectives outlined in SGRDP CB design document
- Attitudes, perceptions, and willingness to adopt energy efficiency technologies
- Perceptions of SGRDP program offerings (e.g. smart thermostats, DR events, CB portal)

8. Results and recommendations from DR voluntary curtailment experiments conducted among USC Microgrid (residential dormitory) residents. Report in MS Word Format containing the following:

- Identification and description of optimal messaging strategies
- Recommendations for future DR event messaging targeted at residential customers.

9. CB10 Customer Post-Ops Survey. Survey in MS Word Format assessed the following:

- CB goals/ objectives outlined in SGRDP CB design document
- Attitudes, perceptions, and willingness to adopt energy efficiency technologies
- Perceptions of SGRDP program offerings (e.g. smart thermostats, DR events, CB portal)

10. Final statistics on Smart Grid Los Angeles Call Center (includes total number and type of customer inquiries/requests.

11. Final report summarizing research findings (includes total number and type of customer inquiries/requests)

7.2 Demonstrations Key Steps

Table below lists the AMI demonstrations and their key steps for completion:

SOPO Demonstrations	Functions To Be Demonstrated	Use Case Scenarios	Key Steps
• **AMI communications and Smart Meter deployment**	1. Demonstrate the initiation of a meter the first time it's installed (Data Collection to Back Office)	This item will be demonstrated within the AMI project	
	2. Demo the benefits of potential "automatic demand response" through AMI versus manual demand response	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR Smart Grid program Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document Designing demonstration scenarios, objectives, metrics

			and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results. Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. Technical report on experimental results on campus related to DR use case studies in DR design Doc.
	3. Demo how AMI supports customer rates/pricing options (related to 3di work)	This item will be demonstrated within the AMI project	
	4. Demo how AMI and data integration with LADWP systems facilitates a Distribution Management System (DMS) and Outage Management System (OMS)	DR-1-Scenario 1: System Operator Integrates Data to Facilitate Outage Management System (OMS)	Use STAS application software to process and analyze real-time AMI data Simulated outage to show-case the effectiveness of the system (Simulated outage will eventually come from MDM) Research report on analytics and experiments

• **Demonstrate Demand Response events in LADWP's Smart Grid Demo Lab Control Center**	1. Demonstrate successful two-way communication with smart meters.	This item will be demonstrated within the AMI project	
	2. Demo control over voltage adjustment where it's needed to manage the demand.	DR-1-Scenario 2: ECC Operator Demonstrates Control of Voltage Adjustment to Manage Load Demand, and Integrates AMI Data to Verify Energy Savings	-Simulate CVR and measure and statistically quantify the effects on the voltage levels supplied to the customers, the overall load reduction downstream of a feeder, and power factor when the voltage at a feeder is reduced within the limits allowed by ANSI. (Voltage Regulator will be manually set based off data collected) -Demonstration on the feeder from one of substations in Chatsworth (Most monitors are installed/some require

			replacement) (Data needs to be collected from Grid 20/20) - Technical report on experimental results - Feedback report for improvements on CVR
	3. Demo two way communications with smart appliances.	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR Smart Grid program (Data will be collected after 1st DR event) Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document Designing demonstration scenarios, objectives, metrics and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results (USC has submitted papers already / currently doing ongoing studies) Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on

			demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. Technical report on experimental results on campus related to DR use case studies in DR design Doc.
	4. Demo customer interface, including updated DWP website to monitor and control demand.		

	5. Demo tools for data and power flow to correct the distribution system (Finalize Chatsworth equipment installation) 6. Demo the impact of distributed generation, storage, and new demand technologies (as they become available) on building, sub-system, and grid level performance. (USC) 7. Demonstrate the power quality impacts of building-to-grid load management systems and optimization on "digitally-dependent" customer applications associated with high-performance computing, laboratory, and medical sub-systems. (USC)	DR-8-Scenario 1: Coordinated Volt/VAR control	Define details of experiments to be conducted to evaluate the capacitor and voltage regulator control for improving distribution system performance Collect data and results from the experiments Improve experiments to characterize the efficacy of the capacitor and voltage regulator control for improving distribution system performance Research report on analytics and experiments

• **Demand response systems in buildings - Building–to-Grid (B2G) technology integration**	1. Demonstrate successful building-to-grid system integration 2. Demo integrated system optimization scenarios across the diverse building portfolio of the campus test bed including: loading and demand management interactions for building sub-spaces and infrastructure sub-systems (water, heating / cooling, etc.). 3. Demo the impact of measurement density (energy use, temperature, etc.) on system performance and optimization. 4. Demo the power quality impacts of building-to-grid load management systems and optimization on "digitally-dependent" customer applications associated with high-performance computing, laboratory, and medical sub-systems. 5. Demo the impact of distributed generation, storage, and new demand technologies (as they become available) on building, sub-system, and grid level performance.	DR-CB-5-Scenario 1: Large commercial customers implements B2G technologies	Task Experimental design and setup Evaluation of DR Demonstration Model configuration and update Report Preparation for USC Campus Microgrid & DDS Engine

• **Communications protocol and prototype Home Area Network (HAN) using WINSmartGrid Technology**	1. Demonstrate capabilities and interoperability of different automation sensing, monitoring and control technologies 2. Demo wireline and wireless networking and communication technologies for HAN 3. Demo how the Integrated automation network and AMI infrastructure support energy usage models, pricing models and demand-response event and messaging	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR Smart Grid program (Data will be collected after 1st DR event) Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document Designing demonstration scenarios, objectives, metrics and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. Technical report on experimental results on campus related to DR use case studies in DR design Doc.

		DR-CB-3-Scenario 2: Customer with HAN participates in DR demonstration program	Receive (from university): Post-test evaluation of the entire DR infrastructure with HAN setup and non-HAN setup. Providing Incremental DR infrastructure evaluation and reporting. Providing reports on the DR infrastructure developed for the project and results of the use of cases with different DR progress.
		DR-CB-4-Scenario 2: Small Commercial Customer with building control system participates in DR Program	

• **Campus test bed microgrid demonstration: React reliably and precisely to a demand response event from the utility by activating procedures to curtail demand.**	1. Demonstrate a full campus-wide integrated Smart Grid infrastructure incorporating both existing and new energy and information systems. 2. Demo targeted load curtailment, using different types of load profiles and customer service requirements, different facility configurations, and different network technologies and strategies. 3. Demo demand response events and processes, highlighting seamless operation of services-based architecture, granularity of load control, cyber security controls, and compliance with customer's load profiles and service requirements.	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR S mart Grid program. Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document. Designing demonstration scenarios, objectives, metrics and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results. Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. Technical report on experimental results on campus related to DR use case studies in DR design Doc.

		DR-6-Scenario 1: Reliable and precise responses to utility DR curtailment events	Receive (from university): Building Audit summary report. Building Strategy progress report . Demo of integrated microgrid command and control center for ADR. Report on Energy Curtailment in Campus microgrid.
		DR-6-Scenario 2: Load demand forecast and curtailment strategy selection using DR software architecture	Define details of experiments to be conducted to evaluate the DR optimization on USC campus micro grid relevant to the DR use case studies in DR design document. Detailed design of demonstration scenarios, objectives, metrics and goals on USC campus microgrid. Technical report on DR Software Architecture on USC campus microgrid. Receive (from university): Research report on additional analytics and predictive models. Updated DDS engine for the USC microgrid. Demo of integrated microgrid command and control center for ADR.

Table 46: CB demonstrations' key steps

7.2.1 Customer Behavior Studies Using the USC Campus Test Bed

The USC campus test bed provided a unique combination of facility types (offices, hospitals, residences, laboratories, and retail); integrated energy services operations; multi-disciplinary research capabilities; and

an exceptionally diverse community of faculty, students, and staff. The lessons learned and best practices developed from CB studies conducted within the test bed (USC campus and surrounding neighborhoods) will be utilized to support and optimize LADWP large-scale Smart Grid deployment.

Methodology

To demonstrate the use case and meet the success criteria for this demonstration, the CB Team applied this use case as an extension of Use Case DR-6 and Use Case CB-7, in order to show an integrated Smart Grid infrastructure that can accept DR control signals from LADWP and perform targeted load curtailment across campus, while considering the curtailment potential available in buildings across campus and occupant preferences.

To demonstrate these use cases and meet the success criteria for this demonstration, the CB Team provided USC Microgrid inhabitants with access to various digital platforms that allowed them to visualize their electricity usage with compelling graphics. Several different tools for various segments, such as small commercial customers, large commercial customers, and residential customers, was available through the Through active participation, the CB Team was able to educate consumers on the importance and impact of monitoring their load demand and also have valuable data collected from how it is impacting the grid. Residential customers have Smart Power Partners, an interactive web portal to help them understand and monitor their energy use. Small commercial customers utilized the Commercial Energy Information (CEI) service while large commercial customers were able to participate in the Building-to-Grid Technology Integration and DR Program. USC also functioned as a large commercial test bed since their facilities have similar energy consumptions. Along with these use case studies, the CB Team also conducted various surveys including a baseline customer survey to assess behavior patterns and other such reports.

Technologies Deployed

Equipment Overview	Total	Installed/ Acquired
Smart Meters on Participating Buildings at USC	41	41
Kiosk displaying Energy Data at USC	1	1

Table 47: Customer Behavior Studies Using the USC Campus Test Bed Equipment List

Success Criteria

The success criteria for the CB Studies using the USC campus test bed include the successful completion of all use cases. Additionally, the CB Project Team will deliver several reports and specifications on the following:

- Identification of effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns

- Identification of key socio-demographic and community structure variables in the Smart Grid adoption process
- Identification of key decision factors in the adoption of Smart Grid related technologies
- Integration of behavioral and social factors into the design and implementation of Smart Grid information architecture, data management, and cyber security systems

7.2.1.1 USC Micro-Grid building occupants participate in energy reduction via voluntary curtailment

This demonstration area was responsible for examining the effectiveness of a competition leveraging energy use feedback enabled by smart meters and an interactive energy kiosk as a framework for reducing energy consumption among university dormitory occupants. It was designed to determine residents' attitudes towards energy consumption, and formulate and analyze strategies for encouraging energy conservation.

Additional voluntary curtailment experiments were conducted among USC micro-grid office dwellers where LADWP examined effectiveness of different messaging on participation in demand response events to:

- Identify load shed possible via customer curtailment in select mixed use buildings
- Obtain occupant input on program, including perceptions of utility, convenience, comfort, and specific actions undertaken
- Evaluate influences of various messaging strategies on participation rate, specific behavior changes made during events, and energy use
- Evaluate commitment strategies on participation rate, specific behavior changes made during events, and energy use
- Use information to inform messaging strategies that will be used as part of Use Cases and future outreach efforts

Methodology

For the first demonstration, 216 smart electric meters were installed throughout Fluor Tower residential dormitory, which allowed building occupants to monitor their energy use at a suite-level. With this information, the residents in Fluor Tower competed for 3 weeks to demonstrate which suite could reduce their energy consumption the most. Prior to this competition, energy usage was monitored for two weeks and residents filled out a baseline study in order to determine the best candidates for the competition. At the end of the competition, participants filled out a final survey, which revealed any changes in their opinions and attitudes about energy use and conservation.

In a second microgrid demonstration, 3,299 USC employees in 41 campus buildings were randomly assigned to one of three groups, a control group, an Anthropomorphism/3rd person group, and an Anthropomorphism/1st person group. Participants received emails encouraging their participation in DR events and the completion of brief online surveys following each DR event. Building-level electricity use data and survey responses regarding DR event participation constituted the study outcomes. Smart meters

were installed on campus buildings participating in this demonstration for energy use data collection. A $500 visa gift card was an incentive for participation. During this demonstration, four emails were sent, each with its own unique message. The first message introduced the "Save Power Event" program and was emailed to participants one week prior to DR event. The second message included animated images of buildings and alerted participants about a Save Power Event occurring the following day and requested participation. The third message also included animated images of buildings and notified participants that a Save Power Event would begin in the next hour and requested their participation. Participants could choose whether or not to take part in the event by engaging in any energy conservation behavior of their choice. The last message asked participants to respond to an online survey that assessed involvement in the DR event.

Observations and Results

For the first demonstration, electricity use in Fluor Tower was 6% lower during competition period compared to baseline. Experiment participants reported engaging in a variety of specific conservation behaviors significantly more frequently during competition relative to baseline. 70% of engaged residents participated in at least one DR event. In the follow-up survey, participants indicated willingness to participate in future DR events and energy efficiency programs. These results provide evidence that real-time smart grid technology-enabled feedback, combined with incentives, can motivate campus residents to reduce energy consumption. By prompting energy behavior awareness via an energy competition intervention that is enabled by feedback from technologies such as smart meters and energy kiosks, normative behavior cues, incentives, and information results in behavioral changes that can cause reductions in energy consumption. Such knowledge can shape strategies for energy conservation programs at the utility level.

For the second demonstration, email notifications 2 and 3 contained the experimental manipulations, which included both text and image manipulations. The survey included a manipulation check to test whether participants recalled the experimentally manipulated messaging in email notifications 2 and 3. Results showed that 73% of controls were accurate, with lower accuracy rates for both Anthropomorphism conditions. Specifically, 46% of Anthropomorphism /3rd and 57% of Anthropomorphism /1st participants were correct, but 80% and 81%, respectively, recalled that the message was anthropomorphized in some manner. This suggests that the anthropomorphism manipulations were distinguished clearly from control conditions, but perhaps not between themselves. Following each DR event, participants were emailed a link to an online survey which assessed participation in the event, factors associated with the decision of whether or not to participate, comfort during the DR event, and likelihood of participating in future DR event.

Building-level electricity use and survey responses regarding DR events participation constituted the study outcomes. Across the two DR events, 64-78% of survey respondents indicated that they participated in the DR event. On average, respondents participated in the event for 1-2 hours of the three-hour events. Across the samples, the mean level of participation was mid-range and did not vary significantly by condition, though the trend was in the expected direction, with highest ratings among the Anthropomorphism/1st condition and lowest ratings among the control group. Participants also reported the likelihood that they

would participate in future DR events. Mean ratings were rather high, and varied across groups in the expected direction, though group differences were not statistically significant. When making a dichotomous comparison between both anthropomorphism conditions versus control, differences were marginally significant.

Ultimately, participation was not enhanced by anthropomorphic messaging, but number of behaviors performed and willingness to participate in the future were. This suggests a nuanced effect whereby anthropomorphic messages differentially impact type of behavior. Among those who have elected to participate, anthropomorphic messaging propels additional change, but it may not have an effect on encouraging participation in the first place. In this sense, it may serve as a performance enhancer.

Success Criteria

The success criteria for this demonstration area include:

- Results of this research yield information that can be used in other areas of the project (success criteria met).
- Contributions are made to the wider body of research regarding the use of social media for utility customer applications, a subject that is just emerging (success criteria not met; Limited CB portal functionality did not include Social media tools due to delayed launch).
- Information shared with Outreach piece of project (success criteria met).
- Information about SGRDP shared with all LADWP employees; obtain buy-in as measured by 10 employees volunteering to be employee ambassadors (success criteria partially met. Outreach to LADWP employees was conducted via LADWP monthly internal newsletter "News You Can Use," and the SGRDP call center provided SGRDP informational materials to LADWP Call Center managers to distribute to staff to educate them about the project).
- LADWP SGRDP System Design: Customer Behavior (CB) Document March 31, 2012 (delivered).
- Information about SGRDP shared with all key stakeholders (e.g., city hall, neighborhood councils) (success criteria met – city council was informed via LADWP public affairs council liaison, and Neighborhood Councils were informed via LADWP customer service teams.
- Customer-facing staffs receive specialized training to handle SGRDP-related queries from customers; demonstrate ability to redirect conversations to benefits of Smart Grid and SGRDP (success criteria met – see call center information).
- Dedicated SGRDP voicemail set up and customer messages responded to in 72-hour period success criteria met – see Call Center information. SGRDP maintained a 24 hour response turn-around time for duration of project.
- Less than 15% opt out rate for meters (success criteria met – 2.19% smart meter installation opt out rate).
- Final survey (2015) of customer attitudes show 65% perceive meters as useful or very useful; 65% perceive smart meters as a good thing or a very good thing (success criteria not met - 46% SGRDP customers willing to accept a Smart Meter.
- Number of calls to CSRs that are specifically to complain about SGRDP represent <33% of calls about SGRDP (success criteria met - CB maintained a SGRDP-specific call center to respond to all customer

inquiries; LADWP call center reps referred callers to SGRDP call center. In total, 591 calls to SGRDP call center were referred/forwarded by LADWP call center (.17% of all calls handled during project).

- Installation of sub-metering in various buildings on USC campus to demonstrate the end-use load profiles for Heating, Ventilation and Air Conditioning (HVAC) fans, HVAC cooling systems, lighting, emergency power and receptacle loading (criteria met)
- Conduct a range of DR strategies to provide the greatest sustainable load curtailment with less than 15% of occupant complaints over a 2 year time period (success criteria not met – no CB demonstrations/experiments conducted that meet this criteria).

The customer interface for energy information that was developed was the web-based CB portal. Due to delayed portal launch, portal design was sharply curtailed; it had much less functionality than originally scoped, and included no social media component. No CB experiments were conducted with the portal due to project time limitations.

7.2.2 Measure and track, against the baseline, attitude and behaviors relevant to EVs and the potential to buy in the future

This demonstration area was responsible for researching the differences and similarities in attitudes, values, and beliefs between distinct target audiences that predict intent to purchase Electric Vehicles and to demonstrate effective messaging strategies to educate different and/or distinct target customer types or groups about factors which will predict purchase and usage of Electric Vehicles. Activities include:

- Customers participating in a survey
- Researching, measuring, and tracking attitudes, values, and beliefs among distinct target audiences that predict intent to purchase Electric Vehicles compared to traditional Internal Combustion Engine (ICE)vehicles
- Demonstrating effective messaging strategies to educate distinct target customer types about factors which will predict purchase and usage of Electric Vehicles
- Identifying key decision factors in the adoption of Smart Grid related technologies
- Integrating behavioral and social factors into the design and implementation of Smart Grid adoption strategies

Methodology

To demonstrate the use cases and meet the success criteria for this demonstration area, the CB Project Team conducted a survey at the household level for a random set of customers in the LADWP service area concerning what cars they own and what cars they may buy in the future.

In the initial baseline survey, a total of 1,000 LADWP customers completed surveys via structured phone interviews. The sample included 500 SGRDP customers and 500 non-SGRDP customers. LADWP mailed EV surveys to customers selected at random. Surveys included 47 questions about customers' perceptions and attitudes towards motor vehicles, including electric vehicles (specifically EVs). Surveys were accompanied by one of two versions of a cover letter that emphasized either social norms ("LA is going electric with

electric vehicles") or financial benefits ("Save money with an electric vehicle") associated with EVs. Surveys batches were mailed periodically; in total, LADWP mailed 25,314 surveys with the social and financial messaging versions evenly split at 12,567. 483 responses were received, for a response rate of approximately 0.02% (265 social, 218 financial).

Technologies Deployed

None acquired/installed.

Success Criteria

The success criteria for the baseline survey demonstration area were to collect and use survey data to develop messages that will be included as part of the subsequently executed Use Cases. Results were to be used to empirically define segments of the population as well as to develop tailored messages for use in Use Cases. Deliverables included:

- Deliver final report on EV driver attitudes, beliefs, and intentions (success criteria met). The deliverable for CB-EV1 demonstration (the EV Survey) was a technical report highlighting LADWP customers' attitudes, opinions and intentions about EV use and adoption.
- Develop enhanced customer communication materials to increase awareness and understanding of increasing availability of EVs, perform public outreach and hold educational forums (success criteria not met).
- Develop enhanced customer communication materials to increase awareness and understanding of increasing availability of EVs, perform public outreach and hold educational forums (success criteria not met).

Observations

General impression of EV was an average of 3.9 out of 5. The likelihood to buy/lease EV was 5.4 out of 10. 5.3 was the average out of 13 for the willingness to pay more for EV ($0 -$6,000 in increments of $500 per scale point). The average sentiment on estimated purchase cost more than gasoline had a mean of 3.8 out of 5. The mean for estimated maintenance costs much more than gasoline car had mean of 2.7 out of 5.

In the observation of impressions of EVs by message type and income group, lower median income (below $75,000) had lower ratings. Among the same income group, people who received the social message had higher ratings.

Results

Respondents had relatively favorable attitudes of EVs, which were marginally higher within the social group in comparison to the financial group. Individuals were willing to pay slightly more than $2,000 extra for an EV alternative to a gasoline vehicle. Respondents who received the financial message were willing to pay substantially more than were those who received the social message.

Relative to gasoline cars, the sample estimated EV maintenance costs to be about equivalent, fuel costs to be lower, and the purchase price to be higher. These responses did not differ substantially across message group. Additional analyses revealed that response across groups differed as a function of income.

Regarding beliefs about EV ownership, the sample agreed that driving an EV indicated they were socially responsible, doing the right thing, and to a lesser extent, acting as a trendsetter for environmentally-friendly technologies. Most respondents also believed that EVs were cutting-edge technology that they associated with reduced environmental impact, and that driving an EV demonstrates care for the environment. These responses did not differ substantially between the message groups.

Groups who were below the sample income median ($75,000) that received the social message had substantially more favorable impressions. No significant response to the social message was observed in individuals with higher-than-median incomes. This suggests that among those with relatively lower incomes, social messaging may promote EV acceptance more than financial messaging. Overall, respondents had relatively favorable attitudes of EVs. This was marginally higher among the social group relative to the financial group. Individuals were willing to pay slightly more than $2000 extra for an EV relative to a gasoline vehicle, and when examining by study group, respondents who received the financial message were willing to pay substantially more than were those who received the social message.

In conclusion, understanding the impacts of different persuasive messaging technique on high-cost green purchase decisions would enable the development of more streamlined and targeted interventions. Such knowledge could then be used to shape strategies for future customer communications at the utility level.

7.2.3 Customer Communications and Education

The primary aim for DRCB-2 scenario 1: Smart Power Partners Program / Pre-Ops demonstration was to evaluate the effectiveness of a web-based energy conservation intervention in reducing home energy use. The secondary aim was to examine the incremental effectiveness of action plan creation in conjunction with goal setting, relative to goal setting alone, in reducing home energy use. Overall, identify set of customer behavior intervention tools associated with the highest levels of customer satisfaction and greatest reductions in overall electricity use. The deliverable was for residential customer to manage energy use using the LADWP Web Portal.

In regards to DRCB-2 scenario 2: CB Portal demonstration, the deliverable for residential customer to use Web Portal to manage home energy use (Enhanced HEI Service). It aimed to

- Educate SGRDP customers about how they currently use energy and how their current energy use patterns impact their electricity costs
- Provide customers with information and tools to understand how to achieve additional cost reductions through a TOU Rate.
- Provide specific customers with tailored messaging

Use case CB-9 was to release LADWP-wide Energy Baseline Survey to assess the following:

- Assess baseline attitudes, values, and beliefs of SGRDP customers about smart meters, energy use, and related technologies
- Obtain customer input regarding preferences for energy efficiency programs
- Obtain information that will be used in to refine tailored messages.
- Obtain information that will be used to refine customer segmentation

Use case CB-10 was to release LADWP-wide Energy Follow-up Survey to assess the following:

- Customers' attitudes, values, and beliefs about smart meters, energy use, and related technologies to provide for identification of changes relative to baseline
- Among SGRDP customers, obtain information on customer satisfaction with SGRDP offerings such as the web portal.

The initial baseline survey was responsible for accessing baseline attitudes, perceptions, and behaviors related to energy management technologies among the LADWP customer base and the final survey was responsible for assessing changes in energy behaviors, as well as attitudes and perceptions related to energy use and management technologies, among LADWP customers.

Methodology

A website-based behavioral intervention was delivered in Summer 2013 to 49 LADWP residential customers in the Northridge area via a custom-built web portal that was seamlessly merged with their LADWP web accounts to support use case DRCB-2 scenario 1. Initially, 3,931 customers were invited to participate. This web portal provided access to new energy management features and included techniques for reducing energy use, including goal-setting and historical and normative energy feedback. The modules included personal energy feedback, normative feedback, carbon footprint audit, badges, and Save Power Events. A description of each module is provided below:

- Personal Energy Feedback: Energy use for the prior two week period displayed in consumption in terms of kWh, dollars (estimated), or pounds of carbon dioxide emitted
- Normative Feedback: In addition to customers' own usage, the average consumption of other SmartPower Partner households was also displayed. When participants perform better than the norm, injunctive normative feedback is associated with usage reduction
- Carbon Footprint Audit: A link to a carbon footprint calculator quiz was provided where participants could enter data about lifestyle choices that contribute to carbon emissions. Reports generated after each quiz to help households identify behavior changes that have an impact on reducing carbon
- Badges: Customers could earn different types of virtual badges for participating in DR events, DR load shedding, reducing overall consumption in a given time period etc.
- Save Power Events: For each DR event, participants received emails the day and an hour before it started. They also received an email after each event inviting them to participate in an online survey

Due to an LADWP web site re-design and the subsequent elimination of the "analyze my personal energy usage" online calculator, it was not possible to compare energy usage between control and experimental groups. There was no data from DRCB2 scenario 1 to evaluate for the effect of customer satisfaction on energy consumption. Enhanced users logged into the goal page an average of 7 times relative to 5 times among Basic users.

Participants were randomly assigned to two different experimental groups and when they logged into their web portals, they could access modules corresponding to their assigned group. In the Simple Goal condition, participants set an energy reduction goal (e.g., energy use by 10%) for two weeks. In the Enhanced Goal condition, participants set an energy reduction goal, and also were guided through a process whereby they selected from a list of behaviors that they agreed to perform in order to achieve their goal. At the end, they asked to log in to the website to check whether they had achieved their goals. They also completed baseline and follow-up surveys about their energy use.

Significant scheduling delays during Operations Phase due to contractor(s) replacement resulted in severe time constraints on CB portal build and deployment. Therefore, no CB experiments were conducted and there are no results to report for use case DRCB2 scenario 2. Online CB Portal/Phase 1 was developed, built and deployed with scaled-back capabilities to support DRCB-2 scenario 2. Customers were unable to monitor their home energy use via the portal in real time, and there were no survey, social media, or gamification/badging functionalities.

Portal promotion and registration outreach conducted via multiple targeted mail and email campaigns in Spring 2016. Portal registration outreach was conducted via multiple targeted mail and email campaigns during Spring 2016, and resulted in 1025 Smart Grid customers signing up. The 2-3 year gap between smart meter installations (Spring 2013 - Spring 2014), and CB Portal launch likely negatively impacted portal registration due to customer churn during that time period, coupled with loss of interest/awareness. Additionally, registration campaign emails were throttled; This most likely prevented numerous customers from receiving the emails. Outreach campaign resulted in 1025 SGRDP customers registering for the portal.

Use case CB-9 was to conduct an LADWP-wide Energy Baseline Survey to assess the following:

- Baseline attitudes, values, and beliefs of SGRDP customers about smart meters, energy use, and related technologies
- Customer input regarding preferences for energy efficiency programs
- Information that will be used to refine tailored messages and customer segmentation

A phone survey company conducted the interviews by phone using a highly structured interview protocol. 1000 customers completed surveys via phone interviews. The sample included 500 SGRDP customers and 500 non-SGRDP customers. A total of 70,529 calls were placed. Of these, approximately 1.4% were completed interviews, 2.3% scheduled call-backs, less than 1% terminated mid-interview, and 9% declined to participate. For 7.9% of calls, the respondent was not available to participate at the time of the call, and approximately 4.2% calls reached ineligible respondents. For the remaining 75.3% of calls, no respondent answered the phone. Approximately 7% of calls were conducted in Spanish.

Use case CB-10 was to conduct an LADWP-wide Energy Follow-up Survey to assess the following:

- Customers' attitudes, values, and beliefs about smart meters, energy use, and related technologies to provide for identification of changes relative to baseline
- Among SGRDP customers, obtain information on customer satisfaction with SGRDP offerings such as the web portal.

The final survey was based on data collected from June 2016 survey (at conclusion of Operations Phase) where a total of 213 LADWP customers completed the survey via phone interviews. The sample included 113 Smart Grid Regional Demonstration Project (SGRDP) customers and 100 non-SGRDP customers. 7107 calls were placed in total. The final survey evaluated relative to the data collected during the 2013 Pre-Ops survey. This comparison provided insights into how customers' thoughts and opinions have evolved based on their exposure to Smart Grid tools, programs, and outreach efforts.

Technologies Deployed

The web portal's initial phase 0 was completed in July 2014, but it was not published due to back-end issues. Phase 1 and 2 was deployed in January 2016 after an approximate 18 months delay. With significantly scaled-back capabilities, customers were unable to monitor their home energy via the portal in real time, and there were no survey, social media, or gamification/badging functionalities. Because key vendors were replaced during the Portal development/build phase, portal deployment was severely delayed and subsequent use case experiments schedule was negatively impacted. Originally, vendor 3Di developed the portal for a hard limit of 52,000 users, without scalability which took place in phase 0. 3Di was replaced by Smart Utility Systems in late 2014, which caused the 18 month deployment delay. Also, there were challenges with integrating the portal with existing LADWP meter data and billing systems, and key LADWP teams were unable to support the project as their focus was on managing a failed new customer care and billing (CCB) initiative. PwC, a vendor involved in both the CCB and SGRDP projects (as Power Engineering Project Management Office) also was terminated, which led to further project delays.

Equipment Overview	Total	Installed/ Acquired
Customer Behavior Web Portal	1	1

Table 48 - Customer Communications and Education Equipment List

Success Criteria

The success criteria for Customer Communications and Education include the successful completion of all use cases. The CB Project Team also developed an enhanced customer website to educate customers about smart grid and energy efficiency.

The success criteria detailed for DRCB-2 scenario 1 were:

- 75% of customers report moderate-high level of satisfaction with energy management options as measured by final follow-up survey CB-10 (success criteria not met - 55% report moderate-high level satisfaction)
- Targeted messages developed based on CB-9 and other pre-Operations surveys applied in Dashboards/Home Energy Reports (success criteria partially not met because demonstrations and experiments involving Home Energy Reports/Dashboard (other than the CB portal) did not take place).
- 75% of customers willing to accept a Smart Meter based on CB-10 survey results (success criteria not met - 46% willing to accept a Smart Meter).

The success criteria detailed for DRCB-2 scenario 2 are stated below, but were not met as there were significant scheduling delays during Operations phase due to multiple contractors being replaced resulted in severe time constraints for CB portal build/ deployment. As a result, no experiments were conducted via the CB portal.

- 35% of eligible customers use the Enhanced Dashboard / applications at least once during first year of release, based on Web Portal Service access activity (success criteria not met because delayed web portal release and scaled-back portal functionality sharply curtailed portal registration and use).
- 10% of eligible customers use the Enhanced Dashboard / applications at least once per month during first year of release, based on Web Portal Service access activity (success criteria not met because delayed web portal release and scaled-back portal functionality sharply curtailed portal registration and use).
- Customers who access the service tools/applications at least monthly use 2% less energy relative to those who do not access the tools/applications monthly, adjusting for demographics and baseline use (success criteria probably not met – CB has no experimental data to support this).
- Accessing the Enhanced Dashboard is associated with increased levels of awareness related to energy consumption as measured by customer surveys (Success criteria not met - In CB10 survey, non-SGRDP customers reported highest level of awareness about energy conservation - 75% say conserving energy very important. 65% of SGRDP customers say it is very important, and 59% of portal registrants say it is very important).
- Of customers who accessed Enhanced Dashboard at least once during SGRDP, 5% submit feedback, comments, or suggestions for improving Dashboard via Dashboard feedback button (Success criteria not met - delayed web portal release and scaled-back portal functionality sharply curtailed portal registration and use).
- Of customers who accessed Enhanced Dashboard at least once during SGRDP, 75% report moderate-high level of satisfaction with LADWP website as measured by final follow-up survey (Success criteria not met – questions specific to LADWP website were not included in CB-10 Smart Grid Follow up Survey).
- Of customers who accessed Enhanced Dashboard at least once during SGRDP, 75% report moderate to high level of satisfaction with energy management options as measured by final

follow-up survey (Success criteria not met - delayed web portal release and scaled-back portal functionality sharply curtailed portal registration and use).

The success criteria for CB-9 were:

- 1000 customers participated (success criteria met)
- Survey assessed demographic information; values, attitudes, and beliefs about smart meters and related technologies; values related to energy use; technology access and use; preferences related to energy management tools; peer-to-peer interaction related to smart meters and energy management (success criteria met)

The success criteria for CB-10 were:

- To have 400 LADWP customers to participate, including 20% of non-SGRDP customers who responded to initial baseline survey and 15% of SGRDP customers overall, including 35% of SGRDP customers who responded to initial baseline survey (success criteria not met).
- SGRDP respondents to complete questions to assess customer satisfaction with SGRDP offerings.
- Data collected from this survey is evaluated relative to the data collected during the 2013 Pre-Ops survey; the comparison provides insights into how customers' thoughts and opinions have evolved based on their exposure to Smart Grid tools, programs, and outreach efforts (success criteria met).
- Follow up survey data will be combined with customer electricity consumption data and web portal usage data to understand how demographic and psychosocial variables relate to energy consumed (success criteria not met: unable to combine survey results with customer electricity consumption data).

Observations

Due to an LADWP web site re-design and the subsequent elimination of the "analyze my personal energy usage" online calculator, it was not possible to compare energy usage between the control and experiment groups to complete use case DRCB-2 scenario 1.

In use case DRCB-2 scenario 2, research showed that customers were less willing to adopt new initiatives unless incentivized to do so; LADWP was limited in its ability to offer incentives because of the bureaucratic nature of LADWP. Previously undetected LADWP marketing email "blacklisting" by over 290 ISPs most likely prevented numerous customers from receiving portal outreach emails during Spring 2016 Registration Campaign. In May 2016, as many as 25% of portal customer outreach emails did not reach the customer. Previously undetected LADWP marketing email "blacklisting" by over 290 ISPs most likely prevented numerous customers from receiving portal outreach emails during Spring 2016 Registration Campaign.

In regards to CB-10, due to configuration issues with the MDM System and delays in the installation of Smart Appliances, some parts of the demonstration area cannot collect any data. However, based on the surveys the CB Project Team sent out, the team observed the following:

- Many SGRDP respondents were not aware they had a smart meter installed at their home: only 27% correctly identified having a smart meter installed. This suggests that the multiple direct mail materials regarding meter installation were not opened or attended to, or forgotten about, by participants.

- The sample also reported low levels of knowledge related to smart meters. Nonetheless, respondents reported neutral to favorable opinions related to smart meters.
- More than two-thirds of respondents were open to participating in Time-of-Use (TOU) pricing plans and Save Power Events.
- Customer preferences for monitoring home energy usage did not indicate major differences in options, but in-home displays were slightly preferred.
- A large percentage of participants (36%) overestimated the amount of energy that could be saved based on their effort. If participants set goals that could not be achieved, they may become discouraged and stop trying. This finding suggested that energy awareness could be improved to help participants set realistic and achievable conservation goals.
- Respondents believed that less than half of their neighbors were conserving energy. This suggested an opportunity to convey social norms about the energy conservation efforts of others that could motivate participants to conserve in their own homes.
- Based on perceived benefits of smart grid systems, the following benefits should be highlighted in SGRDP program messaging: environmental benefits, ability to control usage, and efficiency of the grid system.

Knowledge about Smart Meters was quite limited for both SGRDP and non-SGRDP customers, although overall opinions were generally positive. Little had changed since the 2013 baseline survey. In 2013, over one-third of all respondents had never heard of Smart Meters at all as reported in the baseline survey. Additionally, the survey had a very low survey response rate; only 481 surveys were completed out of approximately 30,000 mailed. The low response rate to the initial survey mailing required additional mailings, which delayed data collection. 55% of customers reported moderate-high level of satisfaction with energy management options as measured by final follow-up survey CB-10. All respondents reported on a number of issues related to home energy management technologies and interfaces, none of the mean ratings differed based on SGRDP participant status.

Compared to baseline survey, fewer SGRDP customers were aware that they had a Smart Meter; only 19% correctly identified having one installed. The acceptability of having a Smart Meter installed also had declined in the last three years; only 46% of respondents in 2016 found it acceptable, compared to 63% in 2013.

In 2016, 63% of SGRDP and non-SGRDP customers were confident about their ability to conserve energy in comparison to other Southern Californians, down from 70% in 2013. Their perceived possible reduction amount declined as well, from 36% in 2013 to 27% in 2016.

Respondents believed they could achieve very high reductions in energy if their household made a special effort to conserve energy by 36% when surveyed in 2013 and in 2016, it declined to 27%. The final survey results on customers' satisfaction with the energy management options offered by LADWP were neutral to satisfied, which was consistent with 2013. There was declining interest in participating in any of these options including TOU pricing plan, free in-home display, or free web portal.

Despite the low acceptance rate for Smart Meters, both SGRDP and non-SGRDP customers recognized some benefits of having one, including reduced electric bills, a more efficient electric grid, and a reduction in disruptive blackouts/brownouts.

In 2016, 75% of non-SGRDP customers were likely to believe that energy conservation was very important, compared to 65% of SGRDP customers. Numerous respondents from both sample sub-groups were taking actions to reduce their energy usage, including turning off lights and other appliances when not in use; upgrading to energy efficient appliances; and turning up AC temperature/turning down heater temperature. Respondents reported on a number of issues related to home energy management technologies and interfaces. None of the mean ratings differed based on SGRDP participant status. Overall, the most frequently endorsed option was the free in-home display, with almost 40% of respondents indicating they were likely or very likely to use it.

Web portal registrants: 3% of all SGRDP customers who were offered access to the free Smart Power Partners web portal registered for it. This customer sub-group is likely to be highly engaged in their energy usage and sustainability-related issues, and early adopters of energy management techniques and technologies.

Home Energy Management Technologies: Respondents reported on a number of issues related to home energy management technologies and interfaces. None of the mean ratings differed based on SGRDP participant status.

For more analysis and observations refer to appendix E (Smart Grid LA Baseline Survey Summary Report) and F (Smart Grid LA Follow Up Survey Summary Report).

Results

During initial goal periods in use case DRCB-2 scenario 1, energy use declined by 0.8% across sample; Basic users increased by 5.9%, whereas Enhanced users decreased by 7.48% on average. These results were not sustained across the 3-month intervention period: participants used 29% more electricity during the intervention relative to baseline. No group differences were observed in this overall rate of change. Participants also were asked to take part in three DR events; usage during DR events was 10-35% lower than usage during temperature-matched non-DR days. Examining DR results by group, usage among Enhanced users was significantly lower than that among Basic users during the first two events (there were no group differences for the 3rd DR event). Enhanced users logged into the goal page an average of 7 times relative to 5 times among Basic users The fact that Enhanced users performed better than Basic users suggests that action planning can have a positive impact on energy use in both energy conservation and demand response.

In use case CB-9, 27% of SGRDP customers correctly identified having a smart meter installed, which suggests that the multiple direct mail materials regarding meter installation were not opened and/or attended to. Sample reported low levels of knowledge related to smart meters, but had neutral to favorable opinions related to them. More than 2/3 of respondents were open to participating in TOU pricing plans and DR events. No significant differences in preferences for home energy usage monitoring technology, but in-home displays were slightly preferred. Participants' overestimated amount of energy they could save (36%) if they made an effort. If participants set goals that can't be achieved, they may become discouraged and stop trying. This suggests that energy usage awareness can be improved so

participants can set realistic, achievable conservation goals. Respondents believed that less than 50% of their neighbors were conserving energy, which indicates an opportunity to convey social norms about others' energy conservation that can encourage conservation behavior. Based on perceived Smart Grid benefits, the following benefits should be highlighted in outreach messaging: environmental benefits, ability to control electric bill, and grid efficiency.

In use case CB-10, where the final survey was compared to 2013 baseline survey, it showed even fewer SGRDP customers who have Smart Meters are aware of it; only 19% identified having one installed. This suggests that the multiple direct mail/emailed materials regarding meter installation (and the web portal launch) were either disregarded or were not impactful. More efficient outreach methods should be explored.

Highlights:

- Given low customer knowledge and declining acceptability of Smart Meters, it is critical to provide clear information on their benefits, including dispelling health and data security concerns, and reiterating benefits such as reduction in electric bills and increased grid efficiency
- In 2016, both SGRDP and non-SGRDP customers are less confident in their ability to conserve energy in comparison to other Southern Californians (63%), vs. 2013 (70%). This suggests an opportunity to utilize key influencers to convey positive social norms about the energy conservation efforts of others that can motivate participants to conserve in their own homes
- Customers' perceived possible reduction amount declined as well, from 36% in 2013 to 27% in 2016. If participants set conservation goals that cannot be achieved, they may become discouraged and stop trying. This finding suggests that energy consumption awareness should be improved so customers are able to set realistic, achievable conservation goals
- Based on perceived benefits of Smart Grid, the following benefits should be highlighted in customer outreach and messaging: ability to control electrical bill, efficiency of grid system, and environmental benefits. Perceived Smart Grid benefits held specifically by Portal Registrants (highly motivated sub-group) should be tested for messaging to the broader customer base as well. These include reduction in greenhouse gasses and support for grid integration of renewable energy.

In terms of what influence does home energy report format have on energy consumption, knowledge of energy use/management information,& customer satisfaction outcomes for use case DRCB-3 scenario 1 and what influence does participant type (Home Area Network (HAN) vs. non-HAN) have on peak load shed during a DR event (as assessed by reduced demand in kW and reduced consumption as measured by kWh during event) for use case DRCB-3 scenario 2, the CB team was unable to conduct survey experiments due to delay in DR hardware deployment and subsequent time constraints. The CB team was not able to determine the following for use case DRCB-3 scenario 3:

a) What recruitment message parameters are associated with the greatest participation rate?

b) How much peak load is shed during a DR event among participants with HAN vs. those without HAN (as assessed by reduced demand in kW and reduced consumption as measured by kWh during event)?

Behavioral science research clearly shows that customers are less willing to adopt new initiatives unless incentivized to do so; LADWP is limited in its ability to offer incentives because cumbersome approval process crosses multiple departments.

Comprehensive CB Call Center Customer Inquiry Data has been manually collected daily from January 1, 2013 to July 12, 2016. Customer address, name, method of contact (phone, email, and letter), inquiry detail, inquiry categorization, concern categorization, SGRDP territory confirmation, and corresponding dates for inquiry and resolution were captured for every inquiry. Tables, graphs and charts were populated with this information.

Excel was the primary technology deployed to capture customer inquiries sent by phone via the dedicated Smart Grid Hotline and the dedicated Smart Grid Call Center email. Excel was used to table and graph customer statistics.

The methodology for capturing this info was executed by a Call Center Administrator, who manually input all customer data into a Smart Grid Call Center Call Log Excel file. Formulas were used to automatically populate tables, graphs and charts that represent many statistics of interest, such as total inquiries, total inquiries by category, total concerns by category, relative percentage of inquiries, relative percentage of concerns, etc. 213 customers completed the survey via phone interviews, including 113 SGRDP customers and 100 non-SGRDP customers. 7107 calls were placed in total. An additional 227 LADWP customers completed the same survey online - 161 SGRDP customers and 66 non-SGRDP customers. 34 SGRDP customers who registered for the Smart Power Partners web portal were surveyed about their experiences using the portal.

Smart Grid LA call log on customer inquiry data can be referred to in the appendix.

In additional, LADWP deployed 6 Customer Outreach videos 1-6. The videos are posted on LADWP.com, social media, YouTube, and CB portal as part of the outreach effort.

7.3 Problems Encountered

Risk Title	Risk Description	Likelihood of Occurrence	Cost Schedule Impact	Risk Consequence	Risk Mitigation
Staffing	Call wait times for LADWP call center are increased	High	Low	• Exposure of LADWP to negative exposure - CSR training impacted due to staffing issue	Customer Service group has implemented a process to minimize wait times. New system has substantially reduced call waiting and increased customer satisfaction. - Resort to Email training instead of class room training

Stakeholder	Various Anti-Smart Meter websites with concerns on LADWP SGRDP/meter deployment	Med	Low	• Failure of a team to meet one or more team objectives, with no material trickle-up impact to the program • Minor schedule or cost overruns, with no material trickle-up impact to the program	Community outreach and education. Will continue to be on-going for the life of the project.
Technical	CISCON go live date officially moved from August 5 to September 5. Impacts Operations web portal development. CB is dependent on the CIS for customer information to populate web portal.	High	High	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns	Continue to track CC&B go-live date and adjust all project dependencies. This is an external constraint and requires cross project integration and coordination. CC&B went live.
Technical	CISCON go-live date September 3rd. Anticipating some systems may not be available during the cutover process. E.g. Customer Connect might be down and CB would not have ability to look up customer information. Also CSR staff will be impacted due to LADWP.com will be down for maintenance.	High	N/A	Delay project schedule.	CB is handling all escalated SG related calls.
Technical	CSR staff will be impacted due to LADWP.com being down for maintenance. Wait time to LADWP call center is over 1 hour.	High	N/A		CB is handling all escalated SG related calls

Staffing	Sub-recipient Invoice payment: Research Lead cannot hire staff until funding from LADWP is received. Lack of staffing delays progress on analyzing pre-operations portal data. Once DOE approves invoices, LADWP will issue check, then USC can fill vacant position.	Low	Low	• Failure of a team to meet one or more team objectives, with no material trickle-up impact to the program • Minor schedule or cost overruns, with no material trickle-up impact to the program	Work with DOE to clear any outstanding questions on this invoice. Re-validate the invoicing process to avoid such delays in the future.
Schedule	Web portal development dependent on CC&B & MDM. CB is dependent on the CIS for customer information to populate web portal.	High	High	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns	Data coming from DR may contain data gaps, errors, or inconsistencies. No further development to portal will occur.
Technical	Messaging studies may be impacted by internal UCLA studies	Low	Low	• Failure to execute messaging study required by SOPO	USC/UCLA are reaching out to resolve the issue, DR research lead is working to resolve the issue.
Stakeholder	Customers have begun submitting damage claims for their appliances related to Smart Meter installation	Low	Low	• Negative media exposure for SGRDP project	LADWP Claims department working to resolve customer issues. Customers have not submitted any damage claims
Staffing	Limited support and availability (ITS) for Web Portal development.	High	High	Delay in go-live due to data integration issues/challenges.	Issues are impacted business processes development and required workarounds. Also, effecting integration of web portal and CC&B. Have a POC in IT - reviewing performance issues

Stakeholder	Meter Lab is stating there may not be any Analog meters for those customers who've opted out of the program.	Low	Low	If appropriate meters are not replaced, customers may escalate issues to city council creating further political issues.	Meter lab will provide Analog meters to customers.
Schedule	USC cost share delay may push project Construction/Testing phase beyond the projected Operations start date if not resolved by the end of February	High	Med	Delays may impact start of Operations phase and accomplishment of SGRDP project objectives.	Impacting baseline survey and storyboard deliverables, these two items are being administered by USC Engagement analyst hiring has been delayed. Cost share has been resolved, CB project team is working on catching up with original schedule.
Schedule / Staffing	Contractual resources may/may not be paid due to expired task order. Current task order has expired and requires amendment.	High	High	Schedule and staffing may be impacted due to resources not receiving funding.	Revised/finalized TO for web portal completion.
Schedule / Staffing	Enhancements to Web Portal may be delayed	Med	Med	Delays with web portal may impact customer experience	CB team / PEPMO is working on resolving contractual issues. Phase 3 out of SGRDP scope.
Stakeholder / Staffing	LADWP opt-out customers have inappropriately received Smart Meters	High	Low	Customer dissatisfaction may lead to negative Smart Grid publicity, financial claim, and legal issues.	CB team is meeting with AMI / Installers to identify resources / timeline for Smart Meter replacement. CB team will also reach out to customers to determine preference.
Stakeholder / Staffing	LADWP Smart Meters have generated an error message and need replacement / fixing.	High	Low	Customer dissatisfaction may lead to negative Smart Grid publicity, financial claims, and legal issues.	Business Process has been established to prevent future error. AMI team has set work requests and informing districts.

Cost / Schedule	USC involvement reduced due to cost constraints and time slips in project schedule	High	High	Reduced involvement may delay data collection from USC	Worked on renewing task order and focus on discussing redline invoices.
Schedule	TOU smart meters cannot be integrated as systems currently exist	High	Med	Option: Abandon demo requirement or find a workaround for data to be retrieved by building an adapter.	No objections from Rates Group, just need to keep them informed.
Schedule	Matthew Gil is on vacation this wk. with pending action item to provide IP impart information to SUS to access of OED, OEM and CC&B.	High	Med	Impacting web development's progress and release date will most likely get pushed back	CB is contacting Matthew's supervisor for assistance and contacting other ITS staffs to provide information pending from Matthew.
Schedule	Architectural requirement for separate servers on different environments; SUS has been running all 3 environments on 1 server, may need to procure servers.	Low	Med	Impacting web development's progress and release date will most likely get pushed back	DWP reviewed SUS design and allow SUS to continue using 1 server for 3 environments. Procurement of servers may not be necessary.
Schedule	rSYSLOG may not be compatible as IT advised CB's servers won't run on Linux	High	High	Would delay schedule if redesign is needed	CS, JPL, CB, and SUS to meet to discuss mitigation plan. Sub-recipient & IT Security determined that it is not warranted to do any more work.
Schedule	Rec'd notification. From SUS on firewall issues, only 1 resource can open firewall and is on vacation.	High	High	Will result in delay, TBD 7/29 Will result in a wk. or 2 delay	Involved parties have assisted and resolved the issue. Plan is put in place should there be required assistance in the future.
Technical	SGRDP servers/system went down 8/11/15- no work can be done	High	High	Delay project schedule	IT mitigated the issue. No additional issues at this time. Four servers moved to new environment. Clean-up completed.

Technical	It has been difficult to obtain continued updates of their dashboard data. Just received update up to Dec. of 2015.	High	Med	Inability to compile reference for TPR	Project manager will continue to follow up for data.
Cost	Post cards are 1 1/2 years old, have customers name, high rate of return expected when they are sent out.	Med	High	Reprint would result in additional costs	Post card had current resident not individual customer names.
Technical	10/06/15 - .34 machine drive vanished 9/17/15: Movement/loss of Physical server while IT is migrating db. on servers without notifying DR, CB, EV resulting in loss of codes in Dev. environment	High	High	Delay technical development/schedule due to the need to re-code lost codes	9/15- Created ITSR 88651for physical server issue (OVN issue) 10.83.25.38. & 410.83.25.34
Technical	Performance issue is impacting CB web portal. ITS advised resource is not committing time resource on project.	Med	Med	Would cause a schedule delay.	9/22/15-Justin will escalate to Emil 12/3/15-Server IT issue has been resolved. No additional issues at this time. Four servers moved to new environment. Clean-up completed
Cost	USC is requesting additional fund due to issue hiring Ellen Dux.	High	High	Would result in additional cost.	Pursued a new task order to sub-contract resource through a vendor.
Schedule	Portal go-live is dependent on CIO sign off. CIO provided sign off, however, now CSD will not sign off until a SLA is in place.	High	High	Would cause a schedule delay	CSD will sign off without SLA but requires Server Alive and NOC monitoring in place while an SLA is negotiated. Portal in place.

Schedule	Undetermined at this time if Staff will accept contract offer by SUS, no available staff to finish remaining demonstrations in CB project	High	High	Would cause a schedule delay.	Behaviorist is on board.
Technical	Issue with firewall/networking on Web Portal QA environment.	High	High	Would cause a schedule delay.	Resolved but did result in a delay in deployment of final modules to portal. No further development to portal will occur.
Schedule	Poor return of registration - cannot meet the project number of acceptance for planned demonstration	High	Low	No activity until DR provides UCLA contact list to CB for outreach. Provided DR deadline of mid-April to provide contact list or demonstration will have to be abandoned due to lack of time remaining on project. Output of demonstration may not be a sizeable representation of service area	4 email blast sent out. Promoted the earning of badges to participate in a prize giveaway as an incentive. Prize is a grab bag full of existing free LADWP branded Efficiency and Conservation items. Impact closing DR-CB3-1 use case / Demo due to schedule delay.
Schedule	Phone survey may not get completed by 6/30/16 if task order does not get authorized for payment by 3/15/16	High	Med	Would cause a schedule delay.	Task order was authorized. Completed survey.
Schedule	Data Collection on Social Media SGRDP Activity (Badges/Shares, etc.…) Twitter/Facebook portion dropped due to limited time remaining on project.	High	Low	3/29 - Twitter/Facebook portion dropped due to limited time remaining on project.	QA environment issue not resolved by deadline. As a result, any remaining demonstrations pertaining to the portal will be abandoned due to lack of time remaining on project. If the QA environment by the end of the month, then

					the badges and giveaway may be implemented, but only to augment to outreach efforts in increasing web portal registration.
Schedule	Post DR-Event Surveys w/ UCLA participants	High	Low	De-scope	Survey could not be conducted because there was no time remaining on project to hold a DR event.

Table 49: Problems Encountered in CB Demonstrations

7.4 Lesson Learned

The major lessons learned for CB includes:

- Outreach (to maximize customer acceptance of Smart Meters and related technology) must be conducted early and often. News regarding the project spreads quicker than you can respond and there are vocal, yet small groups that look to shape the message of Smart Meters into a negative one (mostly focusing on health and privacy concerns). Most of these groups/persons will not even come from the community you service, but they can influence your customer base.
- Anticipating that systems in development will be online when you require them can severely impact the timeliness of your project schedule.
- While customers are interested in testing out new technology (i.e. smart meters, web portal, etc.) a majority will not participate unless an incentive is offered.
- Ensure that an opt-out policy is in place prior to starting outreach. Some customers will choose to opt-out regardless of offering to explain the benefits and to dispel the myths or concerns regarding Smart Meters.
- The biggest challenge is sourcing existing operations to utilize their resources to support a pilot project. All are stretched thin based on other operational commitments, resulting in longer than anticipated response times (i.e. meter installation/removal delayed due to limited staff and install backlog, or communications group providing limited support for outreach).
- Maintaining a separate, dedicated call center for Smart Grid related issues has been far more effective and efficient than training existing CRS staff. The messaging was inconsistent and the training commitment was lacking from the standard Call Center prior to the switch.
- The importance of outreach to maximize participation is critical. One limitation of this project was its low participation rate, which could be mitigated by situating the competition in the context of a broader, more publicized program such as Earth Day. This would garner more support and participation. Also, allotting adequate time and resources towards recruitment and incentivizing is critical.

- Recruiting / communicating with participants via email not efficient and unlikely to scale. Over 3,000 USC staffers were emailed directly as part of the initial outreach effort, but there was a relatively low participation rate. It is likely that situating DR event requests in the context of a broader program would garner more support. Be clear with requests for actions, and protect workplace productivity. Allocate sufficient resources to enhance participation levels. During Operations, messages to promote participation in DR events will be deployed at the USC microgrid and among LADWP residential and commercial customers. Lessons learned here have directly informed DR messaging plans for Operations.
- The low response rate to the initial survey mailing required additional mailings, which delayed data collection. Mailing surveys in DWP envelopes/on DWP letterhead may not be most effective way to reach participants, due to possible negative feelings about DWP. At six pages in length, plus an introductory letter, information fact sheet and a return envelope, the survey packet may have been too long/overwhelming, which also may have discouraged participation. Survey pages should be collated and stapled for clarity.
- Ensure tools and outreach channels (email) are functional and don't squander customer good will and program uptake due to program delays; launch iterative sequential initiatives in a timely fashion for more effective outreach to improve higher portal registration
- Consider scale limitation in RFP process. Avoid changing mission-critical vendors mid-project to reduce the risk of delaying technology/outreach deployment
- Establish process/procedure of all required approval channels to effectively plan outreach, and provide incentives to garner participation in programs. Need to be creative on how incentives are offered.
- Take proactive steps to avoid attrition; the initial sample size recruited should be large enough to account for attrition rates and measures should be taken to minimize time between initial recruitment and program launch, which contributed to high attrition rates (actual launch date was approx. one year after planned launch date)
- Evaluate incentives: Incentives can be effective for encouraging study participation when they are valued by the target population.
- Shorten survey length: Many users only partially completed the baseline and follow-up surveys, which were relatively long. Surveys should be brief and focused to promote completion. Also, randomizing the order of item presentation would assist in rounding out data coverage, especially where imputation methods are available.
- Simplify web portal: Based on visits to each web page, certain web pages appeared to be more valued than others.
- Long gap between customer smart meter installations and portal launch - customer churn during that time, coupled with loss of interest/awareness, negatively impacted portal registration/usage.
- Dedicated CRM software would assist in capturing and organizing customer data and analytics. Use of Excel increased chance of human error in capturing and organizing customer data.

7.5 Conclusion

Web Portal enables customers the opportunity to increase energy savings and lower costs by energy use awareness through an interactive software/applications platform that provides personalized, detail energy

use information. This self-service tool would educate, inform, and help shape the energy usage of customers and allow them a higher level of customer satisfaction and engagement with their utility.

The Fluor Tower competition demonstration provided evidence that real-time smart grid technology-enabled feedback, combined with incentives, could motivate campus residents to reduce energy consumption. Participation in the preceding DR event at USC was not enhanced by anthropomorphic messaging, but number of behaviors performed and willingness to participate in the future were.

The baseline survey (Customer Awareness and EV) results did not capture the impact that recent changes in dropping fuel prices may have on EV acceptance and possible ownership. Finally, knowledge of the EV charging network, locations of charging stations, and charging rates were not captured in the survey. Although previous work evaluated the impact of social influence messaging on low-cost, habitual pro-environmental behaviors, this was the first study to investigate the impact of social influence messaging on attitudes towards an infrequent, high-cost purchase. This was an important area of inquiry because many energy efficiency measures (e.g., solar panel installation, new appliances) fell into the category of infrequent, high-cost purchases with the potential for considerable energy savings. Data was obtained relating to both self-reported (survey responses) and observed behavioral data (survey return rates).

Comparing the final survey to the baseline survey conducted approximately 3 years prior, the Smart Meter awareness decreased with fewer SGRDP customers who were able to correctly identify having one installed at their home. Result suggests that direct mail campaign, emailed material, and web portal launch were not impactful.

The final survey showed that SGRDP customers and non-SGRDP customers were less confident in being able to conserve energy and perceived lower possible reduction amount compared to the results shown in the baseline survey.

Behavioral science research clearly showed that customers were less willing to adopt new initiatives unless incentivized to do so; LADWP was limited in its ability to offer incentives due to its bureaucratic nature.

Details on the data would be reviewed in the appendix - SmartGridLA Call Log, Final Customer Inquiry Data Report, and 7-12-15 along with the Smart Grid LA Call Center Lessons Learned White Paper.

Data obtained for the Customer Behavior Web Portal was analyzed for participation rates and interaction with the various modules provided and with the analysis of Smart Appliances utilizing a HAN. The overall impact of the portal is discussed in the Impacts and Benefits section of this paper.

The table below displays the differences between the conclusions of the surveys:

Take-Away Points	
Baseline Survey	**Final Survey**
Many SGRDP respondents were not aware they had a smart meter installed at their home: only 27% correctly identified having a meter installed. This suggests that the multiple direct mail materials regarding meter installation were not opened, attended to, or perhaps forgotten about by participants.	Compared to the 2013 baseline survey, even fewer SGRDP customers are aware that they have a Smart Meter; only 19% correctly identified having one installed at their homes.
The sample also reported low levels of knowledge related to smart meters. Nonetheless, respondents reported neutral to favorable opinions related to smart meters.	Knowledge about Smart Meters is quite limited for both SGRDP and non-SGRDP customers, although overall their opinions are generally positive. This is little changed since the 2013 baseline survey.
More than two-thirds of respondents were open to participating TOU pricing plans and Save Power Events.	The acceptability of having a Smart Meter installed also has declined in the last three years; only 46% of respondents in 2016 found it acceptable, compared to 63% in 2013.
In terms of preferences for monitoring home energy usage, no major differences were observed, but in-home displays were slightly preferred.	In 2016, 63% of SGRDP and non-SGRDP customers are confident about their ability to conserve energy in comparison to other Southern Californians, down from 70% in 2013. Their perceived possible reduction amount declined as well, from 36% in 2013 to 27% in 2016.
Participants tended to overestimate amount of energy they could save if they made an effort (36%). If participants set goals that cannot be achieved, they may become discouraged and stop trying. This finding suggests that energy awareness can be improved so participants are able to set realistic and achievable conservation goals.	Despite the low acceptance rate for Smart Meters, both SGRDP and non-SGRDP customers recognize some benefits of having one, including reduced electric bills, a more efficient electric grid, and a reduction in disruptive blackouts/brownouts; and
Overall, respondents believed that less than half of their neighbors were conserving energy. This suggests an opportunity to convey social norms about the energy conservation efforts of others that can motivate participants to conserve in their own homes.	In 2016, 75% of non-SGRDP customers are likely to believe that energy conservation is very important, compared to 65% of SGRDP customers. Numerous respondents from both sample sub-groups are taking actions to reduce their energy usage, including turning off lights and other appliances when not in use; upgrading to energy efficient appliances; and turning up AC temperature/turning down heater temperature.

Table 50: Take-Away Points

8 Demand Response Overview

8.1 Summary

New developments in technology on the customer and utility sides of the meter offers the potential for the sophisticated integration of demand-side resources into utility operations to support improved grid reliability, cost containment, reduction of Greenhouse Gas (GHG) emissions, and integration of renewable energy resources. These DR technologies are by definition SG technologies, purposed for active monitoring and dynamic control of electricity usage.

Analytics based on real-time and historical power system data provide utility control center operators with forecasting and visualization tools to increase the accuracy and reliability of load management decisions. Smart meters and advanced building and home automation systems provide customers with unprecedented levels of convenience and control to manage how and when energy is used.

Building and home automation, smart charging and discharging of electric vehicles, distributed generation, and microgrids all create new opportunities and new challenges (such as higher savings and reliability and of course complexity) for grid operations and optimization.

Using facilities at LADWP and our partners' campuses, project test beds, and customer premises, the DR Project demonstrated how some of the most promising new and emerging DR technologies could be applied to best address these opportunities and challenges. Demonstrations included:

- The use of integrated historical and real-time AMI and system data with geospatial analytics software to provide power system control operators with real-time information and visualization tools for making outage and load management decisions, including initiating DR events, and analyzing the response to these events.
- A LADWP Web Portal powered by smart meter data, interactive energy use feedback tools, and customized messaging provides services for customers to become actively involved in changing and improving their energy use habits.
- A program tested with residential customers who are interested in participating in Home Area Network (HAN) demonstrations that will help to define future state offerings for Home Energy Management (HEM) and automated DR.
- A Building-to-Grid (B2G) energy management to describe the interactions of the SG with commercial buildings. DR testing was conducted to optimize load reduction and minimize building occupant negative impacts.
- A campus test bed Micro-grid demonstration to confirm that an integrated SG infrastructure could accept DR control signals from LADWP and perform targeted load curtailment across campus, while considering the curtailment potential available in buildings and the preferences of the facility users.

During the course of the Smart Grid Regional Demonstration Project (SGRDP) Project, 52,000 smart meters and related AMI network technology were deployed to customers in three geographic areas served by

selected LADWP distribution substations. Customers receiving these meters were offered certain services and programs that were enabled by smart meter technology. However, the USC DR team was also offering new services, such as Web Portal energy information services, to the entire LADWP customer base.

The SGRDP included a CB Project that had several interdependencies with the DR Project. The SGRDP-CB demonstrated the impact of the adoption, use, and penetration of SG and home automation integrated technologies on customer awareness, attitudes, and behaviors related to energy use and energy management.

The figure below displays the high level architecture view diagram for DR project:

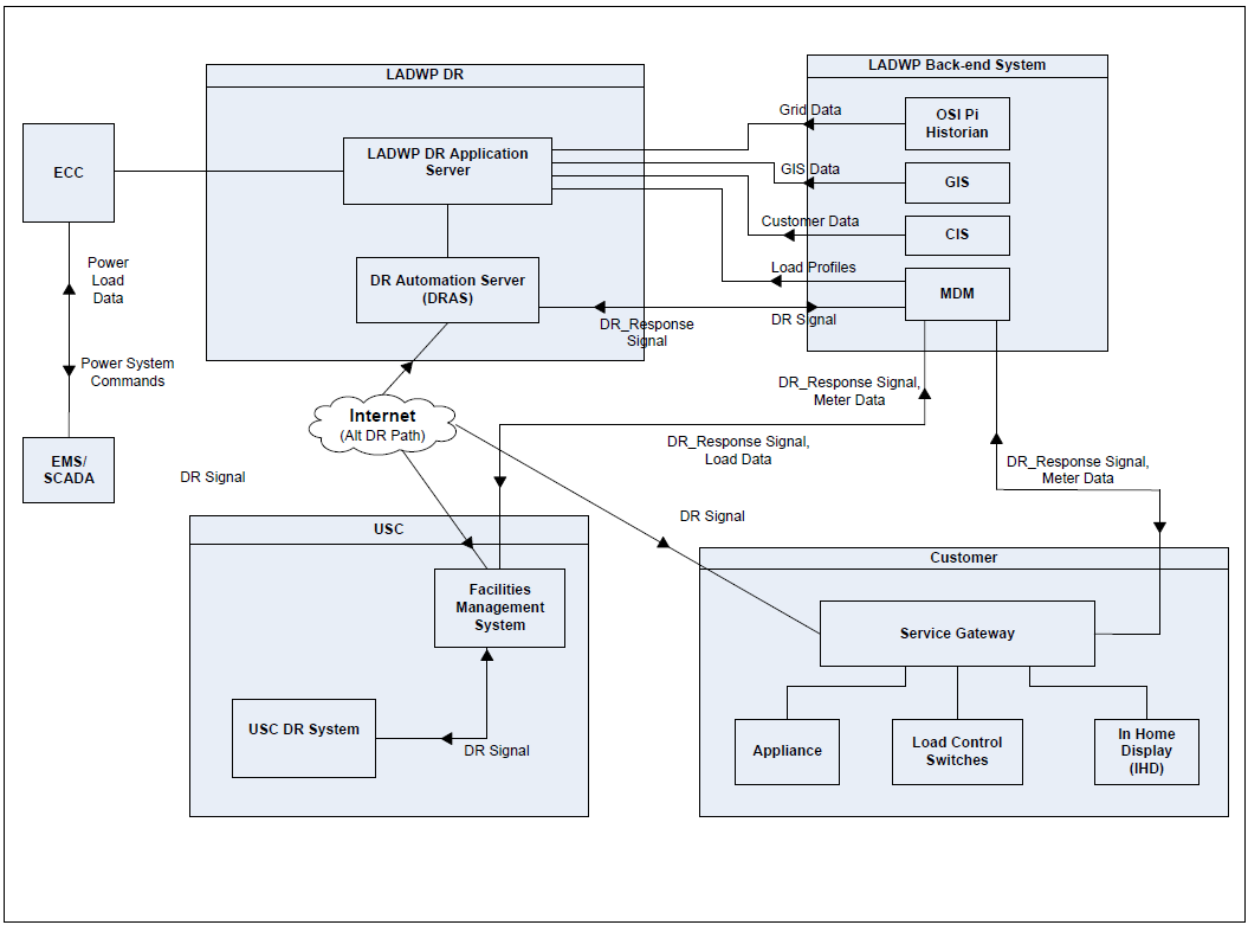


Figure 47: DR Project Top-Level Architecture View Diagram

8.2. Demonstrations Key Steps

The table below lists the DR demonstrations and their key steps for completion:

SOPO Demonstrations	Functions To Be Demonstrated	Use Case Scenarios	Key Steps
• **AMI communications and Smart Meter deployment**	1. Demonstrate the initiation of a meter the first time it's installed (Data Collection to Back Office)	This item will be demonstrated within the AMI project	
	2. Demo the benefits of potential "automatic demand response" through AMI versus manual demand response	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR Smart Grid program Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document Designing demonstration scenarios, objectives, metrics and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results. Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. Technical report on experimental results on campus related to DR use case studies in DR design Doc.
	3. Demo how AMI supports customer rates/pricing options (related to 3di work)	This item will be demonstrated within the AMI project	

	4. Demo how AMI and data integration with LADWP systems facilitates a Distribution Management System (DMS) and Outage Management System (OMS)	DR-1-Scenario 1: System Operator Integrates Data to Facilitate Outage Management System (OMS)	Use STAS application software to process and analyze real-time AMI data Simulated outage to show-case the effectiveness of the system Research report on analytics and experiments
• **Demonstrate Demand Response events in LADWP's Smart Grid Demo Lab Control Center**	1. Demonstrate successful two-way communication with smart meters.	This item will be demonstrated within the AMI project	
	2. Demo control over voltage adjustment where it's needed to manage the demand.	DR-1-Scenario 2: ECC Operator Demonstrates Control of Voltage Adjustment to Manage Load Demand, and Integrates AMI Data to Verify Energy Savings	-Simulate CVR and measure and statistically quantify the effects on the voltage levels supplied to the customers, the overall load reduction downstream of a feeder, and power factor when the voltage at a feeder is reduced within the limits allowed by ANSI. (Voltage Regulator will be manually set based off data collected) -Demonstration on the feeder from one of substations in Chatsworth - Technical report on experimental results - Feedback report for improvements on CVR [This demonstration was not completed due to management's decision to avoid impact to operations.]

	3. Demo two way communications with smart appliances.	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR Smart Grid program. Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document. Designing demonstration scenarios, objectives, metrics and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results. Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. Technical report on experimental results on campus related to DR use case studies in DR design Doc.
	4. Demo customer interface, including updated DWP website to monitor and control demand.		

	5. Demo tools for data and power flow to correct the distribution system (Finalize Chatsworth equipment installation) 6. Demo the impact of distributed generation, storage, and new demand technologies (as they become available) on building, sub-system, and grid level performance. (USC) 7. Demonstrate the power quality impacts of building-to-grid load management systems and optimization on "digitally-dependent" customer applications associated with high-performance computing, laboratory, and medical sub-systems. (USC)	DR-8-Scenario 1: Coordinated Volt/VAR control	Define details of experiments to be conducted to evaluate the capacitor and voltage regulator control for improving distribution system performance. Collect data and results from the experiments. Improve experiments to characterize the efficacy of the capacitor and voltage regulator control for improving distribution system performance. Research report on analytics and experiments. [This demonstration was not completed due to management's decision to avoid impact to operations.]

• **Demand response systems in buildings - Building–to-Grid (B2G) technology integration**	1. Demonstrate successful building-to-grid system integration 2. Demo integrated system optimization scenarios across the diverse building portfolio of the campus test bed including: loading and demand management interactions for building sub-spaces and infrastructure sub-systems (water, heating / cooling, etc.). 3. Demo the impact of measurement density (energy use, temperature, etc.) on system performance and optimization. 4. Demo the power quality impacts of building-to-grid load management systems and optimization on "digitally-dependent" customer applications associated with high-performance computing, laboratory, and medical sub-systems. 5. Demo the impact of distributed generation, storage, and new demand technologies (as they become available) on building, sub-system, and grid level performance.	DR-CB-5-Scenario 1: Large commercial customers implements B2G technologies	Task Experimental design and setup Evaluation of DR Demonstration Model configuration and update Report Preparation for USC Campus Microgrid & DDS Engine

• **Communications protocol and prototype Home Area Network (HAN) using WINSmartGrid Technology**	1. Demonstrate capabilities and interoperability of different automation sensing, monitoring and control technologies 2. Demo wireline and wireless networking and communication technologies for HAN 3. Demo how the Integrated automation network and AMI infrastructure support energy usage models, pricing models and demand-response eventing and messaging	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR Smart Grid program. Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document. Designing demonstration scenarios, objectives, metrics and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results. Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. Technical report on experimental results on campus related to DR use case studies in DR design Doc.
		DR-CB-3-Scenario 2: Customer with HAN participates in DR demonstration program	Receive (from university): Post-test evaluation of the entire DR infrastructure with HAN setup and non-HAN setup. Providing Incremental DR infrastructure evaluation and reporting. Providing reports on the DR infrastructure developed for the project and results of the use of cases with different DR progress.
		DR-CB-4-Scenario 2: Small Commercial Customer with building control system participates	

		in DR Program	
• **Campus test bed microgrid demonstration: React reliably and precisely to a demand response event from the utility by activating procedures to curtail demand.**	1. Demonstrate a full campus-wide integrated Smart Grid infrastructure incorporating both existing and new energy and information systems. 2. Demo targeted load curtailment, using different types of load profiles and customer service requirements, different facility configurations, and different network technologies and strategies. 3. Demo demand response events and processes, highlighting seamless operation of services-based architecture, granularity of load control, cyber security controls, and compliance with customer's load profiles and service requirements.	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR Smart Grid program. Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document Designing demonstration scenarios, objectives, metrics and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results. Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. Technical report on experimental results on campus related to DR use case studies in DR design Doc.
		DR-6-Scenario 1: Reliable and precise responses to utility DR curtailment events	Receive (from university): Building Audit summary report Building Strategy progress report Demo of integrated microgrid command and control center for ADR Report on Energy Curtailment in Campus microgrid

		DR-6-Scenario 2: Load demand forecast and curtailment strategy selection using DR software architecture	Define details of experiments to be conducted to evaluate the DR optimization on USC campus micro grid relevant to the DR use case studies in DR design document. Detailed design of demonstration scenarios, objectives, metrics and goals on USC campus microgrid. Technical report on DR Software Architecture on USC campus microgrid. Receive (from university): Research report on additional analytics and predictive models Updated DDS engine for the USC microgrid. Demo of integrated microgrid command and control center for ADR

Table 51: DR Demonstrations' key steps

8.2.1 AMI Communications and Smart Meter Deployment

See Section 9.1 for all AMI and Smart Meter demonstrations.

8.2.2 Small Commercial Customer Participates in Commercial Energy Information (CEI) and DR Program

LADWP facilitated and developed programs for commercial customers to be actively involved in improving their energy usage habit and engaged in DR programs.

Commercial, Industrial, Institutional (CII) DR Program Technical Services project's goal was to support LADWP's DR team throughout the full deployment and successful implement the DR Pilot Program. Objectives of the Pilot Program project was to audit, identify, provide technical support, evaluate, and sign up for potential participants for LADWP's DR Pilot Program.

The program was targeted specially to commercial customers in order to secure at least twenty customers providing a total of ten MWs of curtailable demand.

LADWP implemented a DR CII Pilot Program solution to validate its ability to automate the acquisition and retention of commercial customer DR program participants, as well as initiate, measure and verify program participation.

Methodology

To demonstrate and meet the success criteria for this demonstration, the AMI team installed smart meters and the Demand Response team integrated historical AMI and system data to find potential customers for

this program. Multiple industries, including Property Management, Entertainment, Education, Healthcare, Museum, Aerospace, Manufacturing, and Retails were evaluated and initial DR processes that were reusable and repeatable were established. Internal and external resources were trained and customers were analyzed. Sites were visited and audited and customers were engaged to participate in the program. The actual DR Program was deployed for the period between 6/15/15 until 10/15/15 and meanwhile 5 DR events were called and 2 surveys from customers were collected.

Technologies Deployed

Customers were not incorporated in the automated building control systems in the initial phase. However, they were able to use internal building control systems to participate in the DR Program.

Success Criteria

The key objectives of this demonstration were to educate customers about their energy use and energy usage patterns impacting their energy costs, provide them information and tools to understand and achieve cost reductions participating in DR program, persuade customers and engage them in the program, and obtain feedback and input to improve the program. The following were the critical success factors of the Demand Response CII Pilot Program Technical Services project:

- Executive support for the program effort
- Use of an experienced program management team using proven life cycle processes
- LADWP Point of Contact serving as the interface between the project team and the business departments participating in this project including Sponsors and Stakeholders
- Timely response (ideally within one working day of the request) for information, data, decisions and approvals
- LADWP dedicated personnel to accompany the project personnel during the data collection and site inspection and provide escorted access to all in-scope sites, buildings, facilities and shared drives to obtain documentation and conduct assessment without delay or impact to the project schedule
- Access to engineers who have knowledge of the nomenclature that describes the LADWP power system substations and its components including protective relaying, bus configurations, equipment ratings and appropriate diagrams/system maps, ideally with a background in system operation, testing and protection/control prints
- Participate in status meetings with the project team, as required
- Help resolve project issues, and escalate issues within the LADWP organization, as necessary
- Streamline approvals for activities that limit the impact on project time or scope
- Provide back-up copies of any relevant programs and data
- Provide seamless access to LADWP staff and documentation
- All documents will be jointly reviewed with LADWP staff
- Adequate customer participation in the site assessments / audits
- Customer support of system upgrades for participation in the Demand Response CII Pilot Program
- Customer acceptance of the Demand Response CII Pilot Program rules and requirements

In this demonstration, with regard to abovementioned objectives and success factors, the following scopes were accomplished:

- Conducted 112 Energy Load Analysis
- Conducted 56+ outreach
- Conducted internal training (PA, CS)
- Conducted 49 site visits/walk-throughs
- Developed 49 Audit Reports
- Conducted 33 Site Validations
- Obtained 26 Customers' agreement to join the pilot program
- Conducted 5 DR Events (7/29/15, 8/13/15, 8/14/15, 9/10/15,10/8/15)
- Worked with Billing and Rates Group for incentive rate process
- Worked with Energy control Center at LADWP (ECC) to define DR Event Dates
- Conducted pre and post DR Event communications with customers
- Conducted internal and external surveys
- Current Score Card indicates 97%

Observations & Results

Through the demonstration, the following templates were provided to LADWP as a deliverable to this project:

- Technical and High level presentation of DRPP
- Audit reports
- Site validation test plan
- Site validation test report
- Program offering survey
- Pilot program operations survey
- Program experience survey
- Training surveys
- Topology
- Customer emails
- Contact information and communications

After running these demonstrations, the AMI data provided 15 minutes tracking of customer energy usage, and based on many available baselines which were available to calculate the curtailments (see figure below), the demonstration selected the "average of 3 latest high loads within the last 10 days of non-holiday non-DR-Event days with morning adjustment" as the baseline.

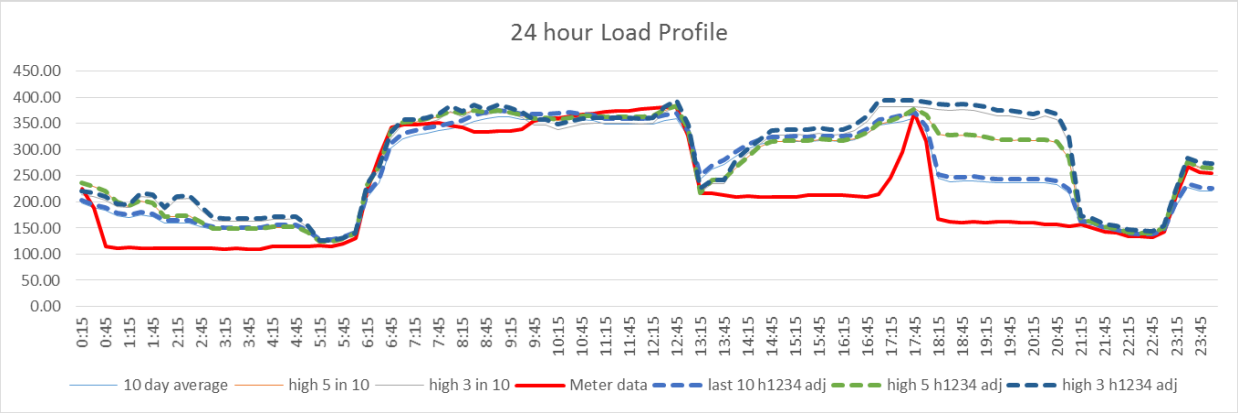


Figure 48 Comparison of different baseline calculations with actual DR energy usage at the day of event

After performing this demonstration, the following curtailment summary was achieved:

Summary Curtailment (kW)	
Confirmed Participants	2,772
XRT Participants	5,962
Total	8,734
Pending Participants	4,640

Table 52: Summary Curtailment

The summary included 14 confirmed participants, 6 Experimental Real-time Pricing participants, and 22 pending customers, and 28 potential customers choosing not to participate.

For the committed customers, below is the list of their committed kW to participate in DR events:

Customers	Industry	Committed kW
Cal State University	Education	100
LA City College	Education	630
LA Harbor College	Education	100
LA Mission College	Education	222
LA Pierce College	Education	241
LA Trade Tech College	Education	100
LA Valley College	Education	100
USC (Non-Incentive)	Education	1,000
LA Live	Entertainment	700
Paramount Pictures	Entertainment	200
Brookfield - E&Y (Non-Incentive)	Property Mgmt.	100
Constellation Place	Property Mgmt.	178
Downtown Properties 311	Property Mgmt.	35
Downtown Properties 601	Property Mgmt.	102
Downtown Properties 818	Property Mgmt.	104
Hines - 10100 Santa Monica	Property Mgmt.	100
Hines - 12100 Wilshire Blvd.	Property Mgmt.	100
Hines - Citigroup	Property Mgmt.	100
Hines - Howard Hughes 6060	Property Mgmt.	101
Hines - Howard Hughes 6080	Property Mgmt.	110
Hines - Howard Hughes 6100	Property Mgmt.	105
Hines - Howard Hughes 6601	Property Mgmt.	100
Hines - Howard Hughes 6701	Property Mgmt.	115
Hines - One Wilshire (non-Incentive)	Property Mgmt.	100
Hines - Playa Vista	Property Mgmt.	100
Hines - US Bank	Property Mgmt.	100
Hines - Warner Center	Property Mgmt.	100
One Hundred Towers	Property Mgmt.	100

Table 53: Committed kW

For the 5 DR events which were performed in 2015, the results of participation are shown below:

Event Characteristics	DR Events				
	7/29/2015	8/13/2015	8/14/2015	9/10/2015	10/8/2015
Customers Called	13	15	15	14	23
Customers Participated	13	14	14	11	20
Number of Hours per Event	4	2	4	4	4
kW Participated	1,682	2,912	2,912	1,782	2,639
kW Performed	2,994	5,213	4,803	4,387	4,673
Performance Ratio	**178%**	**179%**	**165%**	**246%**	**177%**
kWh Performed	11,976	10,426	19,212	17,548	18,692

Table 54: Participation

In summary,

- Total kW per Customer's Application: 4,143 kW
    - (Count does not include USC, Hines One Wilshire & E&Y-approx. 1.2MW, non-incentivized Participant)
- Average kW performed: 5,426 kW
- Total Number of Events to date: 5
- Total Incentives: $47,012

In terms of Survey, the summary is shown below:

Survey	Program Offering	Operational Period
Surveys Sent	33	16
Surveys Received	19	4
Survey Response Rate	58 %	25%
Favorable/Non-Favorable	All Favorable	All Favorable

Table 55: Survey Summary

The Demand Response CII Pilot Program Technical Team approached a wide range of industry types such as:

Property

Commercial Properties, both low-rise and high-rise are typically very good demand response candidates. Commercial properties usually have a management / facilities team dedicated to maintaining and taking care of all the property and tenants needs. They also typically operate and have in place a building automation system that is designed to control HVAC equipment and triggered lighting schedules for tenant occupied space as well as common areas. The facilities' staffs are usually well versed on both electrical and mechanical operations for all the property related equipment and are always looking for ways to reduce their overall energy usage.

Demand responses measures for managed properties are typically centered on the following electrical equipment:

1) Heating, Ventilation Air Conditioning (HVAC) - Air Handling Units, Rooftop Package DX Units, Chillers, and Exhaust Fans & Hot Water Circulation Pumps
2) Lighting - Parking Garage Structure, Main Entry Lobby, Common Corridors, Elevator Lobbies
3) Elevator – Passenger and or Service elevator
4) Escalator
5) Electric Vehicle - Charging Stations

Challenge: Maintaining tenant comfort was a challenge for both property and facility managers, especially when property and facility managers were looking into joining a demand response utility program. Their main area of concern was that whenever space temperature set-points were to be adjusted as part of a

demand response event measure(s). The fear was that they would receive numerous tenant complaints regarding space comfort.

Note: Some tenants also as part of their lease agreement specified space temperate set-point ranges which would need to be met and maintained year-round by the facility management team.

Recommendation: To avoid this type of challenge in adversely affecting a tenant's space comfort, there were a number of demand response strategies that could be adopted by a facilities management team. They were as follows:

1) To fully understand the tenant's space comfort and temperature needs / requirements.
2) To adopt and deploy less aggressive demand response measures in regards to space temperature set point adjustment(s).
3) To focus on other non-HVAC demand response measures. Examples are parking garage EV charging stations, parking garage exhaust fans, Common lighting, elevators, escalators, etc.

Manufacturing

Given their large overall electric loads, manufacturing facilities often have the most to gain out of all CII customers from participating in a demand response program. Many manufacturing plants can be flexible in their operations, making them even better candidates over other industry types. Plants can achieve the financial rewards of participation without impeding production however grid reliability is still the prime motivator, especially those that have experienced blackouts.

Manufacturing plants tend to carefully monitor their operations. However, many plant operators never see a snapshot of their 24-hour load profile taken at 15 min demand intervals. Simply reviewing a plant's energy-use profile can present a compelling case for manufacturers to participate within a demand response program.

Typically, comfort is not a top priority in manufacturing plants. Spaces are usually conditioned to both control and regulate humidity and temperatures in efforts to protect sensitive materials or perishable food products. Maintaining production is generally the highest priority. Opportunities exist to reduce demand, system wide without affecting production.

Demand responses measures for manufacturing plants were typically centered on the following strategies:

1) Moving processes off peak: Many manufacturing plants can schedule processes for off-peak times if given enough advance notification of a demand response event. Other manufacturing plants can change schedules with little notice, shifting large loads to off peak times.
2) Switching to onsite generation: Many manufacturing plants have onsite backup generation and are good candidates for demand response programs that allow the building's load to be shifted onto these generation sources. Switching to backup generation is usually immediate and causes no interruptions to service.

3) Curtailing lighting: Although lighting is one of the smallest loads in most manufacturing plants, the plant can still obtain some benefit by curtailing or dimming lights that are nonessential or located in unoccupied areas.

Challenge: Manufacturing production schedules could at times affect whether a participant would be involved in a called for utility demand response event. As an example: A participant would continue to operate their plant as per production schedule plan and choose rather to opt out entirely of a demand response utility event.

Recommendation: Develop early on with the participant a number of optional, demand response measures both in and outside of production schedules. This would in turn allow the participant to opt in / out, per demand response measure (s) previously identified. Another idea would be to extend demand response notification hours. For an example, a notification window of 48 hours would allow the participant time to shift their production schedule. These two (2) options noted above would provide flexibility for the participant while at the same time enabling them to be still a part of a demand response event, whenever in production mode and or during plant turndown.

Entertainment

The entertainment industry is a challenging industry to successfully and reliably perform demand response with. This is widely due to the fact that within the entertainment industry, scheduling of studio space and event bookings are typically driven by their clients. Clients in entertainment industries include cinema, television, radio, theatre and music.

Production scheduling tends to be the driving force behind energy usage for studios and is the main reason why baseline loads are and can be so unpredictable in nature. When approached to be a part of a demand response utility program, participants feared that they would not be able to keep at their committed demand response level and hence showed poor performance during the demand response season. Despite this, the entertainment industry is energy conscious and always seeking ways to become more sustainable.

The LADWP Demand Response Team had a number of successes in deploying successfully demand response measures for a number of very large entertainment companies based within LADWP's service territory. The success came from developing demand response measures that were flexible in nature and that could shift quickly around production and filming schedules.

A number of demand response measures that were identified for this industry type were as follows:

1) Stage and production lighting sets
2) Space temperature global reset
3) Pre-cooling of the chilled water loop / Pre-cooling of the studio space
4) Chilled water supply / return set-point adjustment
5) Air handling unit fan speed adjustment

Challenge: Scheduling and special event bookings could cause challenges for this industry type whenever a demand response event was called for. This also was very evident when analyzing an entertainment facilities energy usage pattern as baseline loads, which were typically driven by these bookings and were very unpredictable in nature.

Recommendation: Expand on and create a number of demand response measures, which allow for flexibility and for quick set-point adjustments by the participant. Develop a summer, demand response plan with the participant, centered on and around their event calendar schedule would be highly recommended.

Museum

The museum industry can be a difficult industry to completely adopt and comply into a demand response utility program. This is due to museums having a large number of critical condition environments that are designed around housing priceless art pieces and various artifacts, which require specific set-point parameters to maintain integrity. Both temperature and humidity levels are strictly controlled, trended, and alarmed via a building automation system. Any global temperature set point adjustment made as part of a demand response measure is not feasible in this industry.

Museum curators are interested in saving energy and always looking into new ways to lower their overall energy costs. Energy efficiency utility-incentivized programs are good drivers and provided options for museums such as the following:

1) LED lighting upgrades
2) Solar
3) Retrofitting or replacement of aging mechanical equipment
4) Installation of variable speed drives

Challenge: Critical conditioned zones, space temperature, and humidity requirements for maintaining museum artifacts w typically deterred or limited a museum's involvement with a demand response program. A museum's building management system was typically programed for and centered on maintaining a very close control over the space environment for these critical conditioned zones. Typically, these set-point temperatures could not be reset or adjusted in anyway.

Recommendation: Understanding a museums space temperature and humidity requirements prior to developing any demand response measure strategy is highly recommended. It is recommended that demand response measures be not solely HVAC in nature due to sensitive artifacts. Look into demand response measures that do not affect the space conditioning such as:

1) Lighting - Parking Garage Structure, Main Entry Lobby, Common Corridors, Elevator Lobbies
2) Elevator – Passenger and or Service elevator
3) Escalator

4) Electric Vehicle - Charging Stations
5) Cooling tower sand filtration system
6) Parking Garage – Exhaust Fans

Aerospace

Aerospace facilities have critical conditioned locations that are strictly controlled environments per design. Space temperature and humidity set-points are closely monitored for maintaining the integrity of temperature sensitive equipment. Typically, this is what deters or limits aerospace facilities involvement within a demand response program.

Aerospace production schedules could also affect whether a participant would be involved in a utility demand response event. Aerospace production schedules take precedence over how a facility operates. Generally, production runs / production schedules are not able to be shifted outside of a demand response event window.

Challenge: Aerospace facilities generally have data centers present and typically house temperature sensitive equipment that needs to be monitored at all times by the existing building management system. Aerospace facilities offer various levels of HVAC redundancies and operations that tend to be driven by restrictive and tight production schedules. This makes it challenging for this industry type to adopt and deploying demand response.

Recommendation: An attempt should be made to focus on demand response measures other than HVAC. Look into measures like compressed air opportunities and or lighting. Also, allow for ample time in the decision-making processes, as this can be quite lengthy and can cause delays to the demand response project.

Healthcare

Healthcare is one of the most challenging industries to perform and be involved with a demand response program. Strict codes and standards that are enforced by governing agencies such as OSHPD can inhibit what a facility can deploy in regards to demand response measures. Healthcare facilities have a large amount of critical conditioned environments that are strictly controlled and monitored. A number of critical conditioned environments examples typically found in hospitals are as follows:

1) Operating Room (OR)
2) Emergency Room (ER)
3) Intensive Care Unit (ICU)
4) Pharmacy
5) Pre-Op
6) Neonatal Intensive Care Unit (NICU)

Hospitals are typically large buildings with many energy-intensive operations. The largest electricity loads in hospitals are, in decreasing order: lighting, ventilation, and cooling—making lighting and HVAC the best

targets for demand response. Hospitals often have special-purpose rooms such as cafeterias and lounges, in which facility operators can curtail lighting and plug loads without interrupting routine operations.
Most of the hospitals the LADWP DR team encountered had a building automation systems (BAS) that monitors and controls HVAC and lighting systems. All hospitals are required to have backup generation, which facility operators could dispatch during demand response events if it is program approved and State allowed.

Challenge: Healthcare facilities have strict codes, standards, and guidelines that are enforced by governing agencies such as OSHPD. We found that the majority of healthcare facilities analyzed and visited typically had both an aging mechanical and controls infrastructure, making demand response adoption and deployment challenging for the participant of a semi-auto nature.

Recommendation: Look into demand response measures in areas that are not critical conditioned or temperature sensitive environments such as:

1) Main entry lobby
2) General waiting rooms
3) Common corridors
4) Parking garage lighting and exhaust fans
5) Chapel

While conducting site visits, the LADWP Demand Response Technical Team encouraged healthcare facility operators to look into upgrading their aging controls infrastructure. The Demand Response Technical Team shared with them the benefits of adopting a new building energy management system (BEMS). Some of the benefits of adopting a new building management system are as follows:

1) Time scheduling: (Holidays, Daily, Weekdays & Weekends)
2) Equipment and temperature trending
3) Energy monitoring, trending and Alarming
4) Customized HVAC optimization
5) Temperature reset, morning warm-ups and night setback offerings
6) Demand response

Education
School districts and college campuses comprise of diverse facilities of varying age and efficiency, which adds up to significant amounts of space and generally high-energy costs with facility operations. The need to reduce energy is a common theme across the education industry. A recently new, government program known as Prop 39 is aimed at helping schools from K-12 source funding for eligible projects to help improve energy efficiency within school facilities.

During demand response events, schools can reduce energy by adjusting their HVAC set-points, turning off unnecessary lighting and making other temporary changes. Since demand response events often occur in

the early afternoon, typically on the hottest days of the year which is normally early to mid-September when school buildings are often fully occupied and overloaded with students, impact during the period is typically high as most buildings struggle with keeping the temperature at the optimal level.

Challenge 1: It was found that the majority of colleges and universities visited had aging mechanical equipment and or controls infrastructure. Many colleges after conducting these site visits were found to have had two or more building management systems in place. These numerous amounts of BMS layers from various controls manufactures make demand response measure (s) programing challenging and extremely difficult to perform system integration.

Recommendation: Work closely with demand response controls integrator and encourage system wide integration of demand response utilizing open protocols such as:

1) BACnet – Building Automation and Control Networking Protocol
2) LON – Local Operating Network
3) Open ADR - Open Automated Demand Response

Challenge 2: Some schools struggled to keep the temperature at the optimum level during the first two weeks of September of the enrollments period.

Recommendation: Consider having two, load curtailment commitment from selected schools. Look into demand response measures in areas that are not critical conditioned or temperature sensitive environments such as:

1) Main entry lobby
2) General waiting rooms
3) Common corridors
4) Parking garage lighting and exhaust fans

California Clean Energy Jobs Act (Prop. 39) changed the corporate income tax code and allocates projected revenue to California's General Fund and the Clean Energy Job Creation Fund for five fiscal years, beginning with fiscal year 2013-14. Under the initiative, roughly up to $550 million annually is available for appropriation by the Legislature for eligible projects to improve energy efficiency and expand clean energy generation in schools. K to 12 Schools could tap into this source of funding to support new energy projects that encourage demand response program involvement.

Retail

In the retail industry, identifying predictable, reliable, and curtailable loads can be quite challenging. Even though this is one of the more energy dense industries on per sq. ft. basis, implementing energy efficiency measures tend to be an easier and often more of a feasible option for this participant.

Within the retail service sector area, such as Food Service, this particular sector can be a great candidate for demand response. The Food Service industry are often very energy conscious in order to save money. They are also able to perform a number of demand response measures typically within their facility. This provides flexibility to store managers whenever they are in a demand response event.

Challenge: The challenge with deploying demand response with retail clients is to engineer demand response measures that do not affect the shelf life or refrigerated products in anyway and as well as to not take away from a customer's shopping experience / store ambience.

Recommendation: Retail participants typically have constant volume, rooftop package DX units or commonly known as Remote Terminal Units (RTUs) that supply conditioned air to the space below. Focus should be directed at this HVAC equipment for performing demand response measures such as:

1) Precooling the building envelope
2) Duty cycling compressors (15min On / 15 Min Off)
3) Zone space temperature set-point reset
4) Variable speed drive fan speed (s) adjustment

Government

State and local government agencies spend an enormous amount of money per year on energy to provide public services and meet constituent needs. Local governments are challenged with the constraint of tightening budgets, but nearly one-third of the energy used to run typical government buildings can be conserved.

The amount of energy used by commercial and industrial buildings in the United States is responsible for nearly 50 percent of the national emissions of GHGs. Local governments can lead by example and achieve substantial energy cost savings across their facilities, demonstrate energy and environmental leadership, and raise public awareness of the benefits of adopting both energy efficiency practices combined together with demand response to help reduce GHG emissions.

Challenge: Government facilities can have challenges in signing off on demand response measures. This is mainly due to concerns that staff members will or may have issues with demand response measure that affect their comfort zone levels.

Recommendation: Education is vital to keeping staff members up to date and informed of the value of performing demand response measures within their facility. Some of these benefits to perform demand response are as follows:

1) Reducing the environmental impact (GHGs)
2) Supporting of a clean, green working environment
3) Reducing their carbon footprint

Analyzing the MV-WEB interval meter data requires due diligence of the data and customer account information by the Demand Response Technical Team. Accuracy of the information is crucial during the initial stages in identifying those customers suitable as a potential participant and continuing further analysis as the potential participant becomes a CII Demand Response Pilot Program participant.

MV-WEB:

MV-WEB is an existing LADWP online tool that provides commercial and industrial customers secure and reliable access to their load profile data. MV-WEB also provides a cost-effective and easy access to valuable customer load data for account representatives, load research and generation personal, engineers, management, and other internal LADWP staff.

Some of the reporting capabilities of MV-WEB are as follows:

- Peak Day Demand
- 24 Hour Profile Graph
- KVA / Power Factor Graph
- Daily Peaks Graph
- Comparison Graph
- Detail Profile Graph
- Daily Totals Graph
- Peaks Report

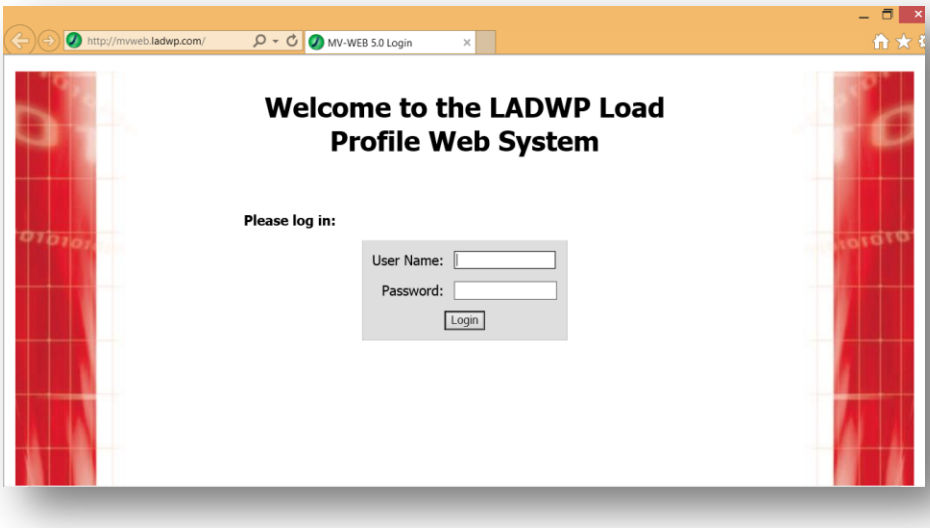


Figure 49: MV-WEB online tool used for meter data analysis

Challenge 1: The information provided on the homepage of MV-WEB is a manual process. Changes to business names or property management may not have been identified to LADWP personnel maintaining

MV-WEB. The customer name, address, and meter numbers in many occasions had to be cross referenced to the customer utility invoices.

Recommendation 1: Verify location and address of the meter on homepage of MV-WEB with Customer Service Unit, if possible otherwise, utilizing such programs online as Google maps to help to identify street addresses combined with the facility's name as additional identification and verification.

Challenge 2: Data for some of the meters require manual download at the customer site due to interruption of wireless services (weak communication, meter communication failures). Conditions such as ongoing construction or meter replacement affect continuous data retrieval.

Recommendation 2: Verify meters with lagging data points in MV-WEB during the initial meter data analysis phase. For those conditions, coordination for manual data download within a reasonable timeframe is essential to conduct the data analysis during the demand response monitoring process. If a lapse in data occurs within the timeframe of a called demand response event, a calculated / estimated load analysis may be required to determine an estimated load curtailment value for the meter with unaccounted for or missing / gaps in data.

Challenge 3: Multiple meters, which include base building meters and leased tenant meters may be listed with the same customer name and address. The inability to distinguish the building baseload meters and tenant leased space may hinder thorough data analysis.

Recommendation 3: For facilities with multiple meters, obtaining an electrical single line diagram enables the Demand Response Technical Team to help better verify the connected electrical load(s) to a specific meter. Since aggregation of load curtailment for facilities is an option, understanding the electrical distribution and confirming that all meters analyzed serve the base building is crucial for a thorough data analysis.

Challenge 4: Missing meter(s) for a given customer may lead to incomplete load analysis and/or maximized load curtailment possibilities during the initial load analysis phase. Customers may inform the Demand Response Technical Team regarding any missing meter information during the outreach, Onsite visit / presentation phase. Corrections to the load analysis prolong the follow up analysis and validation phase of the program.

Recommendation 4: Request a complete list of all customer meters from internal LADWP resources to ensure that all meters are current and accounted for in the MV-WEB system prior to any demand response potential participant outreach activity.

Challenge 5: The MV-WEB software program is heavily utilized by a number of other LADWP internal teams for customer's meter analysis. There are days during the week when viewing and downloading interval meter datasets can be slower than normal, causing lengthy delays with meter analysis. There have been some occasions when MV-WEB has been down and offline due to routine system maintenance.

Recommendation 5: The Demand Response Technical Team have met with LADWP's MV-WEB Rate Technologies and Outreach Team early on in the DR CII Pilot Program to better understand and to be trained formally on the MV-WEB software program. As part of this training process with MV-WEB, the Demand Response Technical Team learned a number of days best suited for viewing and downloading interval meter datasets. (Typically, mid mornings on a Tuesday, Wednesday and Thursday)

Challenge 6: Meter numbers shown on MV-WEB do not display or note the actual meter coding type of the meter physically installed at the customer's location.

Recommendation 6: The Demand Response Technical Team, after capturing images of the customer's onsite meter(s) during the scheduled site visit phase will cross-reference their findings with LADWP's Meter Coding Chart for Self – Contained Meters to identify the actual meter type installed. An example of the Meter Coding Chart for Self – Contained Meters can be viewed on the following page below.



Department of Water and Power
City of Los Angeles
Meter Coding Chart for Self-Contained Meters

METER SIZE (BOLD = PREFERRED VALUE)

VOLTAGE-PHASE-NUMBERS OF CONDUCTORS

MAIN SWITCH SIZE/ (METER TEST AMPS)	120/240 1PH-3W 208Y/ 120 1PH-3W	120 1PH-2W 208Y/ 120 3PH-4W	240 1PH-2W 3PH-3W 480Y/ 277 3PH-4W	480 1PH-2W 3PH-3W	
(TA 5)	3-	103-		403-	obsolete
(TA 10)	5-	105-	205-	405-	obsolete
100(TA 15)	6-	**106-**	206-	406-	
(TA 25)	8-	108-	208-	408-	obsolete
200(TA30)	**9-**	**109-**	**209-**	**409-**	
320(TA 50)	**10-**				
200(TA 50)	11-		211-	411-	obsolete

METER PREFIXES

METER PREFIX DESCRIBES THE TYPE OF METER AND THE TYPE OF SERVICE.
A = AUTOMATIC METER READER
B = AMR WITH MODEM BOARD
C = TIME-OF-USE (TOU)
F = OFF-SITE METER READ MODULE
G = COGEN. INCLUDES TOU & VAR
H = INSOLE METER (PHOTOVOLTAIC)
J = SUB-METER (CUSTOMER'S)
K=STATISTICAL METER
L = PULSE METER
M = MAXIMUM DEMAND
N = NET METER
nD = TOTALIZING n TOU METERS
nT = TOTALIZING n 1 PH METERS
P = POLYPHASE METER
Q = POWER QUALITY METER
R = INTERVAL DATA RECORDER
S = SERVICE FROM 4W DELTA
TDK = STATISTICAL METER (Historical)
U = GENERATOR UNIT METER
W = TOTALIZED BY SOFTWARE
X=TEMP METER
Y = SERVICE FROM 4W WYE
Z = PILOT PROJECT METERS

ABBREVIATIONS

nW = n WIRE SYSTEM
1 PH = SINGLEPHASE
3 PH = POLYPHASE
ITALIC = NON-BILLING METER

METER CODEPLATE COLORS				
	BLUE =	TOU METER	YELLOW =	NET METER & RECORDER
	RED =	KVARH METER	ORANGE =	SUB-METER, INSOLE, & UNIT METER
	GREEN =	COGEN METER	SIL/WHT =	REGULAR METER

EXAMPLES:

F106-	120 V	100 A	1 PH, 2 W	
F#9-	120/240 V	200 A	1 PH, 3 W	DEMAND
F10-	120/240 V	320 A	1 PH, 3 W	400 AMP SERVICE
D9-	120/240 V	200 A	1 PH, 3 W	TOU
J9-	120/240 V	200 A	1 PH, 3 W	SUB-METER
PMD209-	240 V	200 A	3 PH, 3 W	TOU
FK#9-	120/240 V	200 A	1 PH, 3 W	STATISTICAL
P2T9-	120/240 V	100 A	2 - 1 PH, 3 W	TOTALIZED SERVICE
PM411-	480 V	200 A	3 PH, 3 W	OBSOLETE METER
FY9-	120/208 V	200 A	1 PH, 3 W	XFORMER STAR CONNECTION
AND9-	120/240 V	200 A	1 PH, 3 W	NET METER
FH9-	120/240 V	200 A	3 PH, 3 W	INSOLE METER (PHOTOVOLTAIC)
FPMYJ09-	277/480 V	200 A	3 PH, 4 W	SELF-CONTAINED METER
AU9-	120/240 V	200 A	1 PH, 3 W	UNIT METER
R9-	120/240 V	200 A	1 PH, 3 W	LOAD SURVEY (OBSOLETE)
M11-	120/240 V	200 A	1 PH, 3 W	OBSOLETE METER
XFM9-	120/240 V	200 A	1 PH, 3 W	TEMP METER

Figure 50: LADWP's Meter Coding Chart for Self-Contained Meters

Challenge 7: When viewing a customer's interval meter dataset from MV-WEB, it can be challenging to identify missing interval data periods, commonly known as 'Gaps'. Typically, in MV-WEB, a gap in interval data is shown and recorded as a zero. When downloading a dataset as a CSV file for analysis, it can be difficult to quickly identify these missing datasets.

Recommendation 7: The Demand Response Technical Team developed an excel macro that could be quickly customized to help identify missing interval data periods. If a missing dataset is found, a request from the Demand Response Technical Team was made to LADWP's MV-WEB Team to backfill its missing dataset or request assistance from the Meter Shop to have the customer's meter read manually.

Demand Response Notifications:

As per the Demand Response CII Pilot Program requirements, demand response events were limited to a maximum of twelve (12) events. The demand response event windows were typically four hours in length, between the hours of 1:00 PM and 5:00 PM. (Not to exceed one (1) event per day). The demand response event season was between the summer months from June 15th 2015 to October 15th 2015. A Demand Response Event could be called on back-to-back demand response days during this CII Pilot Program season.

There were a number of options that a Participant was given in regards to advance notification of a demand response event. Currently, the Demand Response CII Pilot Program offered three (3) advance notification options for communicating out to a Participant event details, they were as follows:

1) 10 minute notification window
2) 2 hour DR event notification window / Day Of
3) 24 hour event DR notification window / Day ahead

Challenge 1: Participants have shared with the Demand Response Team that some DR event notification notices/emails where not read in a timely manner causing the Participant to be unaware of the DR event.

Recommendation 1: The Demand Response Team developed a number of internal follow-up processes in regards to event notification which was designed to help keep the Participant informed for the scheduled DR event.

First, the Participant is emailed of the event notification that shares important details about the demand response event (Date, Start-time and End-time) and requests the Participant to respond to LADWP's Demand Response Team by a given time and date to confirm their participation in the DR event.

A second email is sent to the participant on the day of the DR event as a friendly reminder, highlighting again the demand response event (Date, Event-start time and Event end-time).

As a third and final follow-up to the DR event scheduled, the Demand Response Team places calls to those Participants who have not responded prior to the event taking place to make sure they are fully informed of the upcoming, DR event that has been scheduled. The Demand Response Team personally answers any questions the Participant might have regarding the DR event to help set their minds at ease.

Challenge 2: During very hot and sustained weather conditions, a number of Participants have chosen to opt out of an entire DR event due to concerns over comfort environments.

Recommendation 2: The Demand Response Technical Team developed a number of DR measures which help to provide options for the Participant during a DR event which have limited to no effect on space comfort levels. This allowed the participant to be still involved with the DR event rather than opting out of an entire event period. The Participant was also reminded of this when the Demand Response Team followed up with their communication outreach event efforts.

Challenge 3: Leading up to a demand response event, Participants often have questions either regarding the event or questions of a technical nature.

Recommendation 3: The Demand Response Team encouraged all participants to call the Demand Response Room directly or email if they had any concerns leading up to or during a demand response event.

Challenge 4: Collecting and downloading a Participants interval meter data via MV-Web on the day after a scheduled DR event for analysis can be challenging because of the time it can take in receiving meter data from field.

Recommendation 4: Waiting forty-eight (48) hours seemed to be enough time to allow for the interval meter data to be received and updated into MV-WEB for analysis. If a small number of meters did not upload their interval meter data sets by this time, the Demand Response Team followed a process and requested that the meters in question be looked into further. There were times that meters needed to be read manually due to weak communications or other issues related to the meter.

Demand Response Events:

Calculating the performance for a DR Event using a baseline that works for all the participants across different industries can be challenging especially for participants that have solar generation. The baseline establishment for any given participant is a simple form of calculation in which the DR Event's consumption is derived based on historical usage from a given number of proceeding days, with the number of days depending on the calculation method. For LADWP's Demand Response Pilot Program, the highest 3 consumption of the last 10 days (from 1:00 PM - 3:00 PM), excluding weekends, Holidays, and prior DR Event dates method was used.

Challenge 1: Choosing the wrong baseline consumption calculation method to show the most accurate electricity usage reduction on the day of the DR Event can result in erroneous measurements and misrepresentation of DR data results.

Recommendation 1: Research all baseline consumption calculation methods for DR programs and analyze which one works best for a particular industry and participant to determine the extent of reduction by estimating what the consumption would have been in the absence of curtailment, and comparing such predictions with observed load usage during curtailment.

Challenge 2: Analyzing the dataset from MV-Web and converting it into a report to show the curtailment amount by repeating the same calculations multiple times for each meter can be tedious and time consuming.

Recommendation 2: Create a macro in MS Excel using a format that allows the user to insert the downloaded dataset from MV-Web and automatically create a report using the results.

Challenge 3: Participants are able to enhance curtailment amount for the Event Day by ramping up their usage more than normal in the morning before the event starts. Whether the participant pre-cools or begins to unload hours before the event, the end result for reduction amount will not be accurate.
Recommendation 3: To improve accuracy and reduce bias, use a normalization factor for the morning of the event (take the average of 09:15 – 12:00) divided by the average of highest 3 of 10 days for the same time period.

Challenge 4: Occasionally, a meter may not have data available in MV-Web, even 24 hours after an event resulting in a delayed report.

Recommendation 4: Shortly before an event check to see if each meter has current data and if not, determine what could be causing the delay in being uploaded in order to see if that meter will need special research for this and future events.

Challenge 5: Some Participants has solar generation capability which makes it difficult to rely on their committed load curtailment and schedule.

Recommendation 5: Create a separate pool of DR Event Participant which has solar generation capability. Identify or project the timeline which load curtailment may be achieved (i.e. under a normal circumstance, solar generated energy may be depleted when energy is needed from LADWP, participant's consumption should be curtailed to an agreed upon DR measure).

Potential Participants:
The Demand Response CII Program Pilot Team has worked hard to develop a series of actions and steps that are required to be taken in order to achieve both program success and maintain participant involvement within the Pilot Program. There have been many key processes developed along the way, which no doubts have led to the growing success of the Demand Response CII Pilot Program for 2015.

A number of detailed processes have been established for both internal LADWP groups and as well as external and customer facing (Participants). The CII Pilot Program follows a detailed Process Framework that can be viewed in section 6. The process activities listed within the Framework document are as follows:

- Identification phase
- Socialization / Scheduling - Outreach
- Auditing – Technical

- Confirmation
- Event and Monitoring
- Incentive and Rebates

The Demand Response CII Program Pilot Team has also conducted research into various demand response tools and software systems (SaaS) that are available from third parties who would aid in and enhance a program's success like demand response. These various tools and advance system solutions are required once a pilot program transitions on and move into a full deployment phase. Program tools like **Smart Mobile Workforce.**



Figure 51: Smart Mobile workforce

Smart Mobile Workforce (SMW®) is a single integrated platform designed to increase efficiency, compliance and safety of workers. It provides details including and not limited to Work Order, Expense, Time Sheet, Asset, Dynamic Field Forms, Training & Learning, Notifications, Enterprise Collaboration, with built in operational analytics and dashboard.

A number of challenges and recommendations from The Demand Response CII Program Pilot Team have been documented below.

Challenge 1: Based on a number of early conversations with Potential Participants, the Demand Response Team has found that some Potential Participants seem to be more at ease whenever their account representatives are present for the initial, onsite meeting with the Demand Response Technical Team.

Recommendation 1: The Presence of an LADWP Premium Account Representative during the initial Demand Response CII Pilot Program presentation showed to set at ease a Potential Participant's comfort level during this first time engagement as questions do arise that were not demand response related, such as billing.

Once the communication lines were established and trust was built between the Demand Response Technical Team and Potential Participant, all communication dialogues was then documented within a communication log, noting topic of discussion and any follow up action items. The communication log was managed by the Demand Response Technical Team and electronically filed on LADWP's share drive for internal reference purposes.

Challenge 2: It can be challenging for the Demand Response Technical Team to gain internal access to a Potential Participant's most current information for records such as:

- Current Contact names
- Current Telephone numbers
- Current Meter numbers

Recommendation 2: The Demand Response Team found solutions and developed techniques to find and locate a Potential Participant's most up-to-date contact details and meter information. The team used a number of internal tools and met regularly with various LADWP business teams such as the Premium Accounts group and Rates and Billing as part of the Potential Participant identification stage.

Challenge 3: The Potential Participant's presentation deck is based upon information provided by internal LADWP resources such as the Premium Accounts group as well as utilizing a software tool known as MV-WEB. Circumstances can arise in which information provided was found to be either partial to actual conditions, which can lead to invalid assumptions within the Potential Participant's presentation deck. Examples such as missing meter listings in MV-Web or buildings within a campus that no longer exists under the current Potential Participant's account.

Recommendation 3: The Demand Response Technical Team member assigned to a particular Potential Participant reached out to the Premium Accounts Representative that was assigned to the account to show the Potential Participant's presentation deck to make sure all information within was accurate. Any changes then were made quickly to the deck before the presentation was to be scheduled.

Challenge 4: Potential Participant site walks conducted by facility management personnel that are not familiar with various electrical systems and perhaps lack the authority to approve system load curtailment capabilities can cause delays.

Recommendation 4: The Demand Response Outreach Team requested and confirmed that whenever possible facility management personnel who are knowledgably about the various facility systems and who are authorized to approve demand response measures be present during this onsite walk with the Demand Response CII Technical Team.

Challenge 5: There have been occasions when a Potential Participant had documentation to share with the Demand Response Team when they are out in the field conducting the onsite visit to develop the agreed to demand response measures.

Recommendation 5: Using a mobile tablet tool which utilizes a software program like Smart Mobile Workforce would help with this important, early information gathering process phase and limit the amount of return visits that the Demand Response Team would have conducted due to missing Potential Participant information. The Potential Participant could also have access to this tool to upload site details and submit images of mechanical equipment & nameplate data.

Challenge 6: A number of Potential Participants are not yet ready for Semi-Auto Demand Response for various reasons. Some have building automation related issues and others have concerns related to operational and onsite staffing.

Recommendation 6: These Potential Participants want to be a part of a demand response program. Our recommendation would be for the 2016 DR year to adopt and implement an Automated Demand Response Technical Solution utilizing OpenADR 2.0 that does not require full automation at the Potential Participants end.

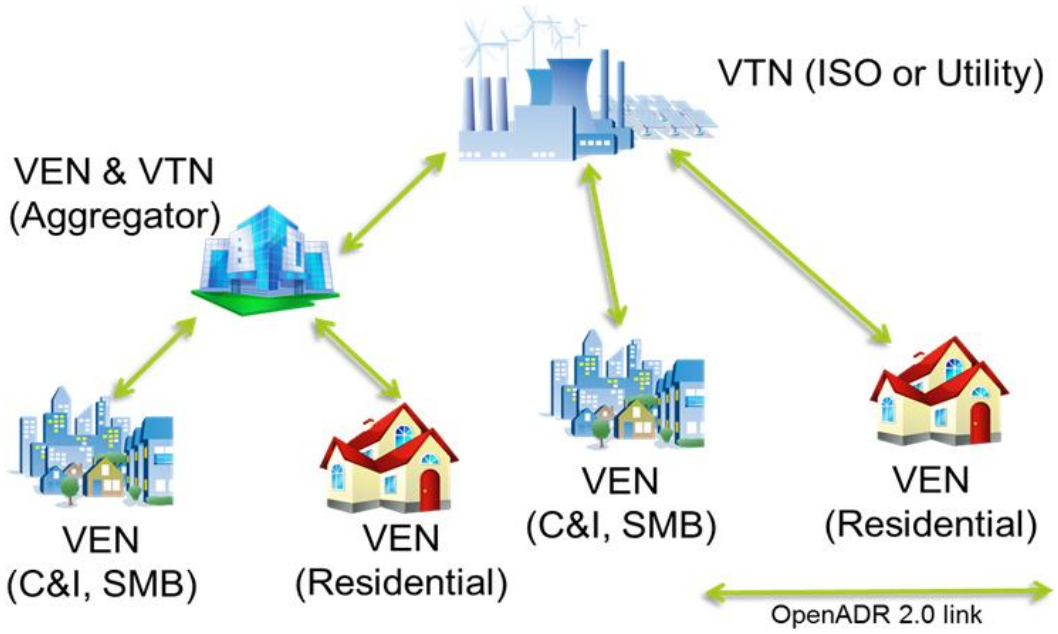


Figure 52 OpenADR 2.0 link

8.2.3 Data Integration, Load Forecast and DR Optimization for Demand-side Load Management

This demonstration aims to evaluate various forecasting models' ability to predict power consumption time series.

Methodology

In this study, the Autoregressive Integrated Moving Average (ARIMA) Statistical Model, Static, and Data Driven/Dynamic Models are used on the same dataset and compared in a principled basis under some assumptions that are made due to the specifics of the datasets and required output as outlined below:

- The available power consumption data is divided into 15 minute intervals.
- The prediction temporal horizon is either 1 PM - 5 PM (16 intervals / values corresponding to heavy consumption hours) or from midnight to midnight (96 intervals / values entire next day).
- The use of Mean Absolute Percentage Error (MAPE) to assess the predictive accuracy of our models.
- The dataset's power consumption values aggregated values over a varying degree of granularity. Namely, our dataset consists of values aggregated over 1,000, 5,000, 10,000 and 50,000 measurements.

The ARIMA Statistical Model is dynamic time series consumption model to make predictions. ARIMA is a model that requires historical interval data for training before it can be used for predictions. The

timestamp and kWh usage value for a customer for a certain periodical time in history are the only feature presented for training.

Static models for time series were used as baseline models to determine what the consumptions would have been for a specific curtailment period. They require the kWh consumption values for recent time intervals in order to predict the subsequent time intervals. The method's accuracy was tested in terms of MAPE to make predictions for two horizons: 16 (4 hours) and 96 (24 hours).

Aside from static models being evaluated, data driven/dynamic models were also evaluated. Data-driven dynamic models used machine learning with a set of feature vectors provided for each consumption interval to train the model and they often improve in accuracy with larger training datasets. The Regression Tree Algorithm for training the data-driven dynamic model was used to make predictions. The setup features for the data-driven dynamic model is shown below referred to as Waikato Environment for Knowledge Analysis (WEKA) as it uses the WEKA java library.

- First Setup: Time of the day, day of the week and consumption.
- Second Setup: Fact that if it is a holiday or not (0/1) and consumption.
- Third Setup: Time of the day and consumption.
- Fourth Setup: The day of the week and consumption.
- Fifth Setup: Only consumption.
- Sixth Setup: Day of week, time of day, temperature from SUS dataset and consumption.
- Seventh Setup: Temperature from underground dataset and consumption.
- Eighth Setup: Temperature from SUS dataset and consumption.

For more information on ARIMA and parameters used for the static forecast models and data-driven dynamic models, along with observations from different parameters used refer to Appendix AS.

Two challenges emerge when applying time series forecasting models for predictive analytics to a large utility service area:

1) Cost – training a predictive model per customer is computationally costly
2) High error – the variability in the energy usage per consumer causes the prediction models to have high errors

The challenges can be addressed by aggregating data from multiple customers into a single "virtual customer" in order to reduce the prediction error by reducing the temporal variability. Given a daily clustering configuration, predictions were made for each cluster individually in the demonstration. The proposed clustering algorithm can be referred to in the Appendix AS.

Observations & Results

ARIMA model's findings did not portray a good forecast performance outside of predicting the usage for 1-5 PM on the same day given the data until 1 PM. Results showed high standard deviation in majority of cases and further degraded the performance.

The California ISO (CAISO) baseline model algorithm provided by the DDS Java library performed relatively well. Other baseline models such as Southern California Edison (CASCE) and New York ISO (NYISO) were evaluated as well. NYISCO performed better than CAISO with small error and small standard deviation.

The best scenario was seen using CASCE out of the static models. Setups where holidays, day of the week, and consumption were considered from the data-driven dynamic models achieved the best performance and may be due to the fact that the day of the week has a huge impact and correlation with the consumption behavior. Therefore, these setups can outperform other scenarios.

The demonstration concluded ARIMA as the best candidate out of ARIMA, CAISO, NYISO, CASCE, and WEKA for the smallest error and standard deviation which made the predictions more reliable. As for the best model where predictions were made for the entire next day, NYISO performed better and was recommended for next day predictions. The best model with regards to having the lowest processing time, NYISO, CAISO, and CASCE had the lowest and similar processing time among the models that were evaluated in this demonstration.

8.2.4 Demand Response Optimization Using Service-Based Software architecture

New developments in technology on the customer and utility sides of the meter offers the potential for the sophisticated integration of demand-side resources into utility operations to support improved grid reliability, cost containment, reduction of Greenhouse Gas emissions, and integration of renewable energy resources. These DR technologies are by definition smart grid technologies, purposed for active monitoring and dynamic control of electricity usage.

Analytics based on real-time and historic power system data provide utility control center operators with forecasting and visualization tools to increase the accuracy and reliability of load management decisions. Smart meters and advanced building and home automation systems provide customers with unprecedented levels of convenience and control to manage how and when energy is used.

Building and home automation, smart charging and discharging of electric vehicles, distributed generation, and microgrids all create new opportunities and new challenges for grid operations and optimization.

The goal of the DR Project was to demonstrate how some of the most promising new and emerging DR technologies can be applied to best address opportunities and challenges using facilities at the University of Southern California main and health campuses. Demonstrations include:

- The use of historical and real-time AMI to provide power system control operators with real-time information tools for making outage and load management decisions, including initiating DR events, and analyzing the response to these events.
- Demonstrate automated DR by (i) enabling the USC campus testbed Micro-grid accept DR control signals from LADWP, and (ii) performing automated targeted load curtailment across campus, while considering the curtailment potential available in buildings and the preferences of the facility users.

Methodology

To demonstrate and meet the success criteria for this demonstration, the LADWP Demand Response team worked with University of Southern California Team. The USC team developed a “Demand Response

Decision Support" and "policy engine" to assist facility operations in determining how much load to curtail based on Campus Consumption Forecasting (CCF) with the use of machine learning predictive methods that are encapsulated as part of DDS. An Automated Programing Interface (API) was delivered to LADWP. The software architecture (policy engine) provided a recommendation in selecting the buildings to target for curtailment, continuously monitoring the effectiveness of obtaining the curtailment target, and dynamically adapting its recommendations to ensure the curtailment target was met. This enabled the team to precisely and reliably respond to utility DR events with an appropriate forecasting and curtailment strategy.

Technologies Deployed

An overall communications platform was developed to support decision making after a demand response event has been initiated. The DR Software Architecture contains Information Integration Pipeline (IIP), Database of historical training data for consumption forecasting, Collection of machine learned models for consumption prediction, Collection of machine learned models for curtailment prediction, DDS, and Policy Engine.

DDS is a Java library that the USC DR team has developed to integrate machine learning techniques for consumption and curtailment prediction as well as for consumer and DR strategy selection algorithms. DDS is responsible for managing datasets required for training and prediction, storing and selecting trained models, providing an interface for admins to train and test models, and offering a web service endpoint for automated responses for training and prediction.

The data sources involved in this process are considered as "Big Data". Big data is a broad term for data sets so large or complex that traditional data processing applications are inadequate. The data resources are listed as followings, and are scalable to the level of City of Los Angeles:

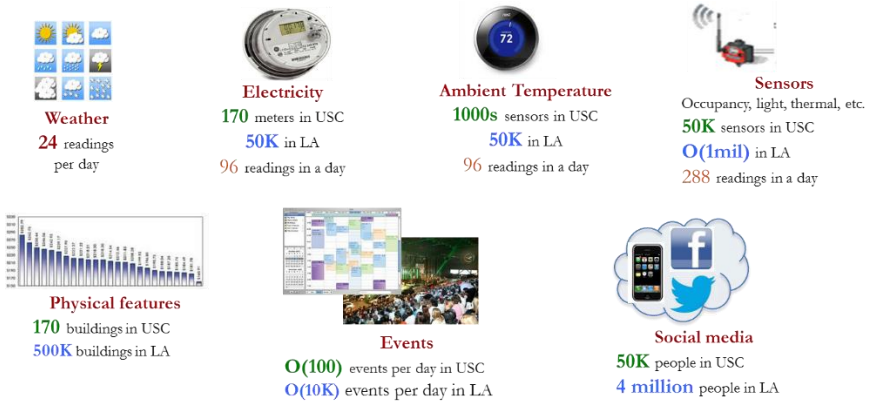


Figure 53 Data and deployed Technologies

Most of the data from the sensors are in real time (every 15 minutes or less).

Success Criteria

The success criteria for the Demand Response team included the successful completion of all related use cases. Successful communication between Facility Management System (FMS) and the ability to remotely control and monitor individual buildings according to received curtailment strategies during DR periods.

DDS was integrated with the FMS control center as a Representational State Transfer (REST) service which received as input consumption data and DR requirements (e.g., duration, start time, available buildings and strategies) and returned the recommended list of building-strategies to be used to reach the desired curtailment target.

The DR Software architecture demonstrated the microgrid acting as a utility operations center in making DR decisions, and assisted the USC FMS operations in determining when and how much load curtailment on which buildings should happen. DDS also continuously monitored the effectiveness of obtaining the curtailment.

The functional target of this demonstration was as follows:

- Demonstrate a full campus wide integrated SG infrastructure incorporating old and new information systems
- Demonstrate targeted load curtailment using different types of load profiles, customer service requirements and facility configurations and strategies.
- Demonstrate DR events and processes, highlighting seamless operation of service based architecture, granularity of load control, cyber security and compliance with customers' load profile.

DDS has internal components and their functionality is provided in the table below:

Components	Functionality
USC DDS Java Kernel Library	Perform training of Java consumption models using provided training datasets Perform training of Java compliance models using provided training datasets Perform prediction of consumption values using provided Java consumption models and prediction datasets Perform prediction of compliance values using provided Java compliance models and prediction datasets
Data Access and Loading	Access external, DWP and project data sources to retrieve latest values. Transform incoming data formats and units into a form that matches the DRDR schema, and load data into DRDR database Allow bulk and periodical access and loading.
DRDR Database & Model Store	Provide a database with the appropriate schema for storing and querying training and prediction datasets, and a storage location for trained models.
Data Querying & Model Storage	Performs queries over DRDR databases to return *consistent* training and prediction datasets that are aggregated and gap filled. Supports storing and retrieval of Java model objects.
Administrative Interface	(Browser based) Administrative interface for On-demand model training & testing, Comparison of accuracy of model results, and configuring standard models.

Components	Functionality
DDS Web Service	Web service implementation that allows training and prediction using the DDS Java kernel libraries for consumption and compliance. Performs querying of training or prediction data, executing model training and model storage, and invoking model predictions.

Table 56: DDS Components and Functionality

The decision making for Demand Response is Big Data driven process and the process is demonstrated as below:

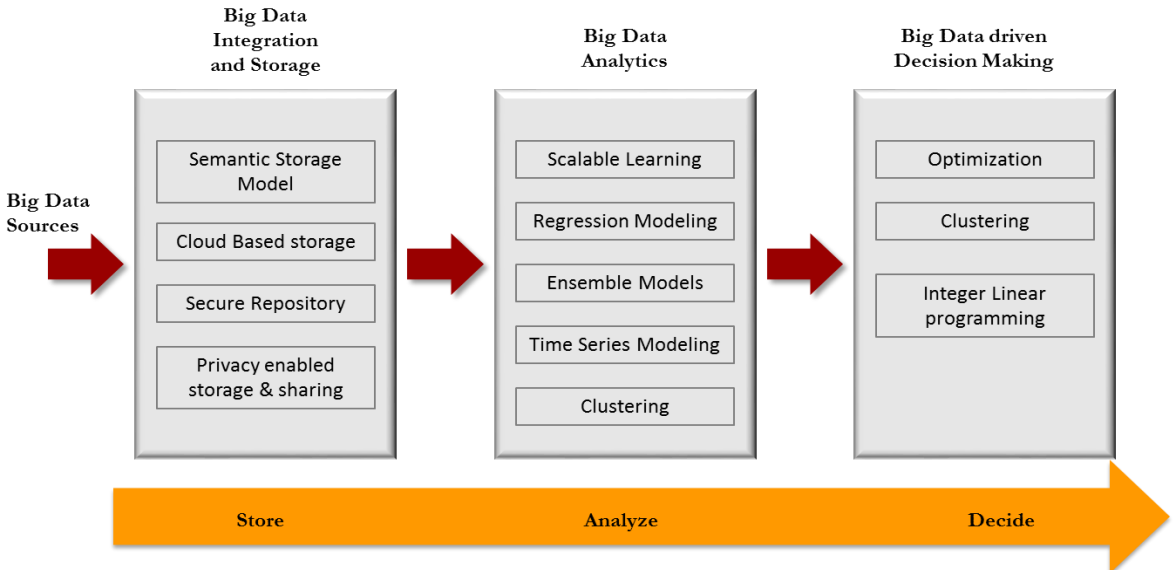


Figure 54: Big Data driven Decision making for Demand Response

Consumption models were used as baseline models by utilities. Three baseline model algorithms are provided by the DDS Java library: California ISO, New York ISO, and Southern California Edison. More technical details and reference can be referred in the appendix from Final Technical Report USC on Use Case DR-6.

Observations

Customer selection and curtailment strategy:

One of the problems solved in this demonstration was selection of customers and curtailment strategies that should be adopted to achieve the targeted curtailment value. The solution provided was integer linear programming formulation which could handle the challenges of scalability, fairness, and adaptability.

Demonstration challenges:

There were several challenges which made this demonstration complex and the solution unique. These challenges were:

- Continuous batch information ingest for analytics and diffusion.

- Provide data storage security, owner-controlled data sharing, data integrity and audit, assured file deletion and secure search.
- Detect semantic vent patterns in real time that necessitate DR
- Predict curtailment and reduced consumption during DR
- Predict consumption in the absence of real time data from some sensors.

For more observations, refer to Appendix M.

Results

For satisfying this scenario 1 of DR Optimization in Campus Test Bed Micro-Grid Using Service Based Software Architecture, the following targets were delivered:

- USC demo/control center JACE controller can query the DRAS (Demand Response Automation Server) in a timely schedule.
- LADWP can send out requests for DR, provided the information includes time and duration
- USC control center can receive the DR event and notify selected USC facility personnel
- An acknowledgement is sent from USC to LADWP
- USC control center can monitor the load curtailment and building conditions.
- FMS can monitor complaints from building occupants.
- Record the effect of the curtailment for future references. (including temperature, demand, lightings, etc.)
- Comparisons can be made between buildings to improve DR strategy.
- USC facility operator can select and observe the current load status and kW.
- Facility operator can be notified of available Load curtailment and forecasted consumption through automated software architecture.
- Facility operator can pull up the historical consumptions and forecast consumptions.
- Facility operator has a list of curtailment options available and can choose different curtailment strategies or request a set to be suggested.
- The effectiveness of curtailment is available to the operator and it is updating during the DR event to improve the performance and accuracy.
- All DR activities are monitored and recorded for future use, and are available to LADWP for informing the operations at the utility.

For satisfying DR-6-Scenario 2, the following targets were delivered:

- USC Facility operator can observe the current load status of the campus from the USC demo control center. This displays the real-time load (KW) on different buildings and equipment within them, the current consumption demand (KWh) from the different buildings and the forecast consumption (KWh).

- The facility operator can look at information at different spatial granularities of rooms/buildings/regions of campus based on available information. This information is provided by the Semantic Information Repository and the machine learnt models component.
- The facility operator uses static knowledge of available generation capacity (simulated) and the forecasted consumption to determine that a curtailment is necessary on the campus.
- The facility operator is assisted in curtailment selection by the DDS component of the USC software architecture.
- DSS can provide different categories of curtailment strategies, along with an estimate of the level of curtailment from each, how soon the curtailment can be achieved, the probability of success and the impact on user comfort.
- The operator can individually select from the different curtailment strategies or request a set of strategies to be suggested by DSS to meet the required curtailment.
- Once the selection of buildings is performed, the curtailment policy is automatically executed.
- The effectiveness of the curtailment is monitored by the operator by observing the current load in the different buildings on which curtailment has been started and matching it against the expected curtailment from those buildings.
- Execution of the direct control operation is verified through observations of load and equipment activity.
- The operator can observe if the curtailment is not going to be achieved.
- All DR activities are monitored and recorded to allow future analysis by the operator and for automated learning by DSS. This is also provided to LADWP for informing DR operations at the utility.

8.2.5 Communications protocol and prototype Home Area Network (HAN) using WINSmartGrid Technology

Home Area Networks (HANs) will connect appliances, on-site renewables, and storage devices in homes to the grid for access to real-time energy usage and pricing information, and providing the ability to react to demand response events from LADWP.

HAN has the potential to become a significant resource for demand side management impacting home owners, utilities and smart grid vendors. HAN allows remote monitoring and control of home appliances and gadgets. In this project various HAN technologies have been developed that enable intelligent control of electrical loads inside customers' premises in response to utility signals. The control and monitoring system can manage individual electrical load or aggregate loads. Control and data flow is secured by industry approved encryption schemes, and automatically provides protocol translations, electricity usage records, and electrical load states. HAN has been successfully integrated with Demand Response Management System comprising of Demand Response Automation Server (DRAS), Demand Response Data Repository for scheduling and managing demand response programs based on OpenADR specification.

An open, standards-based, and flexible architecture for HANs is important to ensure longer life as the technology evolves. This demonstration involves protocols and prototypes for communications, and sense-and-control and information-based systems for HAN using UCLA WINSmartGrid technology.

Methodology

This demonstration showed an integrated demonstration of Smart Grid technology and operations for DR (e.g., to manage load in peak demand conditions). DR test bed sites and appropriate tools were chosen to investigate a full range of user infrastructure environments, including residential, commercial, institutional, medical, retail, and light industrial. Forecasting power consumption of the system based on historical trends and the system's characteristics were part of the DR's approach to monitor and manage the system's load. DR technologies were being designed and deployed on the customer and utility sides for active monitoring and dynamic control of electricity usage for this SGRDP. On the customer side, building and home automation, customer load response, customer behavior, smart charging and discharging of EVs, and microgrids all create new opportunities and new challenges for grid operations and optimization. On the utility side, analytics based on real-time and historic energy consumption data, real-time distribution system data, and customer behavior information provide utility control center operators with forecasting and visualization tools to increase the accuracy and reliability of load management decisions. Smart meters and advanced building and home automation systems provide customers with unprecedented levels of convenience and control to manage how and when energy is used.

Using facilities at Los Angeles Department of Water and Power (LADWP) and our partners' campuses, project test beds, and customer premises, the DR Project demonstrated how some of the most promising new and emerging DR technologies could be applied to best address these opportunities and challenges.

During the course of the Smart Grid Regional Demonstration Project (SGRDP) Project, 52,000 smart meters and related AMI network technology were deployed in three geographic areas served by selected LADWP distribution substations. Customers who received these meters were offered certain services and programs that were enabled by smart meter technology. However, the USC DR team was also offering new services, such as Web Portal energy information services, to the entire LADWP customer base.

In this use case, a demonstration scenario was tested with residential customers who were interested in participating in Home Area Network (HAN) demonstrations that would help to define future service offerings for Home Energy Management and Automated Demand Response.

Success Criteria

Section 4.3.3.3.3 defined the success criteria for scenario #2 of use case DR-3 as the following:

1) DR results are accurately recorded at the equipment and whole-house levels
2) 80% of customers with functional appliances/equipment participate in at least one DR event
3) 50% of customers with functional appliances/equipment participate in at least one third of DR events
4) Load shed among HEM customers is greater, on average, than load shed among customers in Use Case DR-CB 3, Scenario 3 (customers with smart meters & Enhanced Dashboard but without HAN/HEM)

5) Analyses conducted to identify customer factors and customer preference settings associated with participation and amount of load shed for different times of day
6) Achieve per customer peak reduction of 5%
7) 75% of customers are moderately to very satisfied with program (as assessed by surveys)
8) 50% of customers reported discussing program with others as assessed by surveys

Progress vs. success criteria

1) All DR results and equipment operations have been recorded at the house level. (Complete)
2) More than 80% of selected DR appliances/equipment has participated in DR event. (Complete)
3) More than 50% of HAN appliances/equipment has participated in at least one third of DR events. (Complete)
4) This part of demonstration is not performed due to unavailability of customer portal and their participation in DR-CD, scenario 3. (Cannot be completed due to Customer portal unavailability)
5) Customer preference settings were not available at the time of performing this demonstration due to unavailability of customer portal and this criterion is not performed in our demonstration. (Cannot be completed due to Customer portal unavailability)
6) Achieve per customer peak reduction of 5% (Complete)
7) 75% of customers are moderately to very satisfied with program (as assessed by surveys). (CB unable to conduct survey experiments due to delay in DR hardware deployment and subsequent time constraints)
8) 50% of customers reported discussing program with others as assessed by surveys. (CB unable to conduct survey experiments due to delay in DR hardware deployment and subsequent time constraints)

Additions to success criteria and their demonstration achievements

In this use case, the demand response team achieved demand-side load management by integrating data and implementing load forecasting and DR optimization. Small commercial customers with HAN systems participated in DR demonstrations and were convinced to opt in to DR programs. The customer automated systems in HAN environment were able to communicate with utility systems during the automated DR.

Key objectives of residential demand response project were to develop and implement HAN technology stack that would demonstrate:

1) Heterogeneous networking to support plug-n-play capabilities of control nodes in the network
2) Robust and reliable two-way protocol translation
3) Secure networking across the entire home area network
4) REST based architecture using XML or JSON data payload
5) Interface of Home Area Network with OpenADR Demand Response control and monitoring pipeline
6) Support electric load- 'shed', 'shape' and 'shift' DR strategies

Communications protocol and prototype Home Area Network (HAN) using WINSmartGrid Technology

Home Area Networks (HANs) will connect appliances, on-site renewables, and storage devices in homes to the grid for access to real-time energy usage and pricing information, and providing the ability to react to demand response events from LADWP.

HAN has the potential to become a significant resource for demand side management impacting home owners, utilities and smart grid vendors. HAN allows remote monitoring and control of home appliances and gadgets. In this project various HAN technologies have been developed that enable intelligent control of electrical loads inside customers' premises in response to utility signals. The control and monitoring system can manage individual electrical load or aggregate loads. Control and data flow is secured by industry approved encryption schemes, and automatically provides protocol translations, electricity usage records, and electrical load states. HAN has been successfully integrated with Demand Response Management System comprising of Demand Response Automation Server (DRAS), Demand Response Data Repository for scheduling and managing demand response programs based on OpenADR specification.

An open, standards-based, and flexible architecture for HANs is important to ensure longer life as the technology evolves. This demonstration involves protocols and prototypes for communications, and sense-and-control and information-based systems for HAN using UCLA WINSmartGrid technology

Methodology

To demonstrate these use cases and meet the success criteria for this demonstration, the Demand Response team integrated the historical and real-time AMI and system data for making outage and demand-side load management decisions. Additionally, the LADWP Demand Response team provided HAN and HEM services to customers to better educate them about how interactive energy management applications work and will also be a means of providing them with the ability to set preferences to control how and when their appliances and other equipment use energy. Also, a Home Energy Management program was made available to those interested in a HAN demonstration. The energy consumption data under the home energy management program was used as a data source for implementing load forecasting and load curtailment.

Planned Approach to Evaluation, Investigation and Development of HAN solution

In order to successfully demonstrate Demand Response through HAN a number of technology, hardware, software, database, process / business logic and deployment test bed related issues had to be researched and inspected. This study was very important as the solution had to meet a number of essential requirements such as LADWP's IT architecture, security, and customer privacy, need for automated Demand Response and interoperability with other technologies, applications and systems of the project.

Data repository had to be designed to store smart meter, appliance, and DR participants' data in order to separate the data from LADWP databases on account of non-availability of required schema support, avoid pollution of data of LADWP databases and facilitate a service topology that is isolated from LADWP production IT infrastructure for security purposes.

As pertinent Demand Response software / applications were not available within LADWP IT infrastructure, it was necessary to design and develop appropriate software. Service-Oriented Architecture (SOA) based design was selected for the Demand Response software as SOA facilitates enterprise agility by way of supporting agnostic technology stacks, mitigating configuration constraints, providing flexibility to re-combine functions to meet changing requirements, simplifying integration of new functionality with minimum disruption, promoting operational scalability, and bolstering loose coupling with database and system technologies.

Custom automated HAN control units had to be designed and developed as control units with native OpenADR support were not available off-the-shelf. Since it was decided to use OpenADR for Demand Response control units were developed on a single board computer (SBC). The embedded system based on WinSmartGrid technology has on-board OpenADR client and capable of executing demand response signals received directly from the server.

WiFi (IEEE 802.11 b/g/n) communications and networking was selected over ZigBee, Z-Wave and Insteon technologies. During evaluation it was found that ZigBee, Z-Wave and Insteon had the following shortcomings:

- Interoperability between technologies from different vendors
- Communication range was short and inconsistent compared to WiFi
- WiFi was more reliable
- Licensing of Z-Wave and ZigBee was costly than WiFi
- WiFi provides larger and robust bandwidth which was essential to connect 10-12 control units to the network as would be required in a typical residence

Technologies Deployed

Equipment Overview	Total	Installed / Acquired
Refrigerator	29	29
Direct Load Control Device	29	29
Lighting System	15	15
Smart Gateway	29	29

Table 57: Communication Protocol and Prototype Home Area Network using WINSmartGrid Technology Equipment List

In order to demonstrate OpenADR based demand response in residential space, the HAN should be capable of receiving the DR signals from the utility or service provider and effect intelligent curtailment of participating electrical loads. Since suitable technology which could do this is not available, the entire technology stack was developed under this project. The important units in the HAN are the smart gateway and the load/appliance control units. The smart gateway acts as the bridge between the HAN and utility

networks and the load/appliance control units establish and manage the DR strategies for the residential electrical loads.

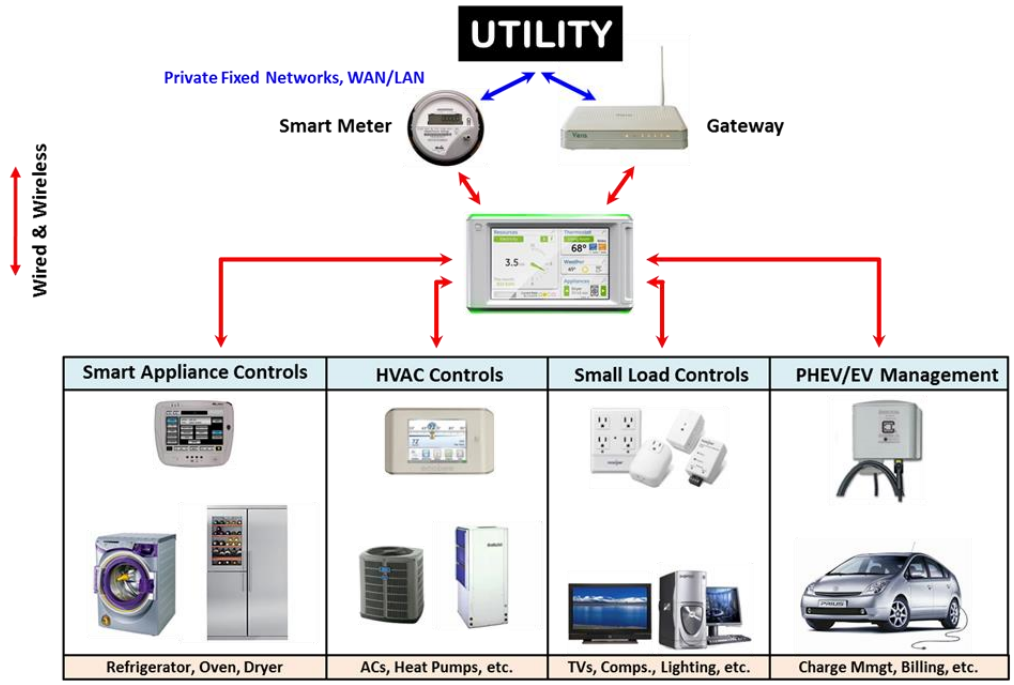


Figure 55: Communication Network

Embedded system

An organic embedded system was developed to support communications, data / protocol translation, control and monitoring of the HAN. The key modules of the embedded system developed for the smart gateway, load / appliance controller and the host are as shown in figure below.

The embedded system developed runs on Linux platform. The key features of the system are

a. Intelligent control and monitoring – registration of control units with the gateway, auto-restart, auto-reconnect, data logging, data purging, communication over HTTPS transport, authentication and authorization

b. On-board data persistence to log connectivity, energy consumption and demand response event related data. Intelligent self-manageable buffers were implemented

c. Control protocol translation facilitates the conversion of DR event data into control unit operations – switch off/on, dimming, and modify cycle times

d. Client – server communications is based on client-side polling as this model simplifies the network address translation issues of control units that are invariably deployed behind the access point firewalls.

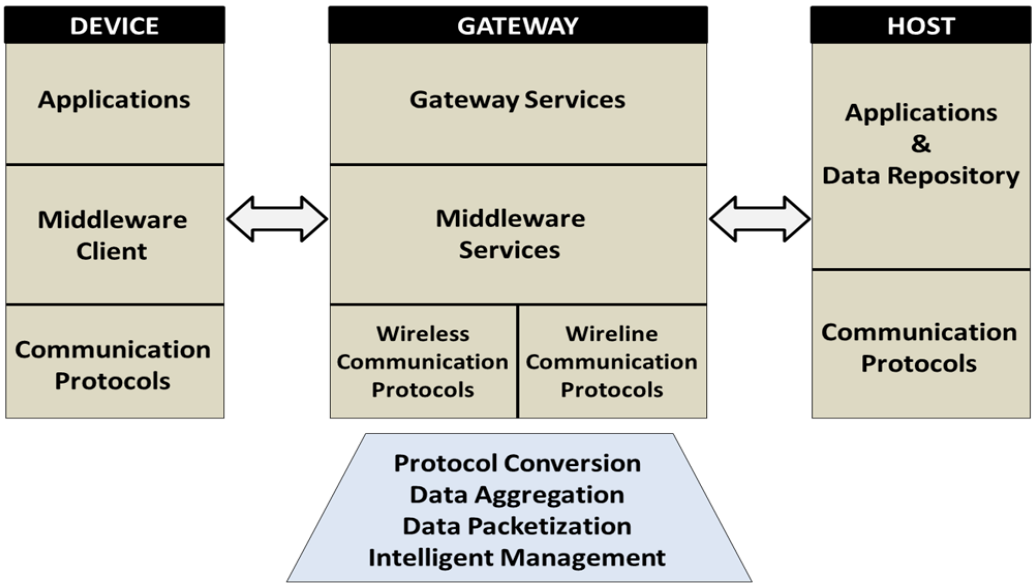


Figure 56: HAN embedded system modules

Smart Gateway

Salient features of the smart gateway:

a. Acts as a network endpoint inside the customer premise that maintains two-way communication between the Utility Network and HAN.

b. Assists commissioning of HAN and DR account registration with the utility DRMS

c. Manages energy consumption profiles of registered loads that are capable of self-metering

d. Provides network connection through wired Ethernet, WiFi, and/or ZigBee

e. Establishes network connectivity with network enabled electrical loads appliances, digital thermostats, load control units, electrical outlets and switches, etc.

f. Assists customer preferences management for registered electrical loads. Preferences set to particular day, particular time of day, and type of response to utility DR event

g. Manages the entire lifecycle of OpenADR signal. Loads will be shed, shaped, or shifted

h. Manages the acknowledgement channel with DRMS to update the scheduled response to the utility company's DR event

The smart gateway connects the HAN to external network systems, such as the utility company's network, and manages all devices within the HAN. The gateway has six primary functions: network communication and appliance management, storage of electricity usage records and electrical load states of appliances, privacy protection of the end users' energy data, DR signal response generation, and management of consumer preferences. Smart gateway architecture schematic is shown below.

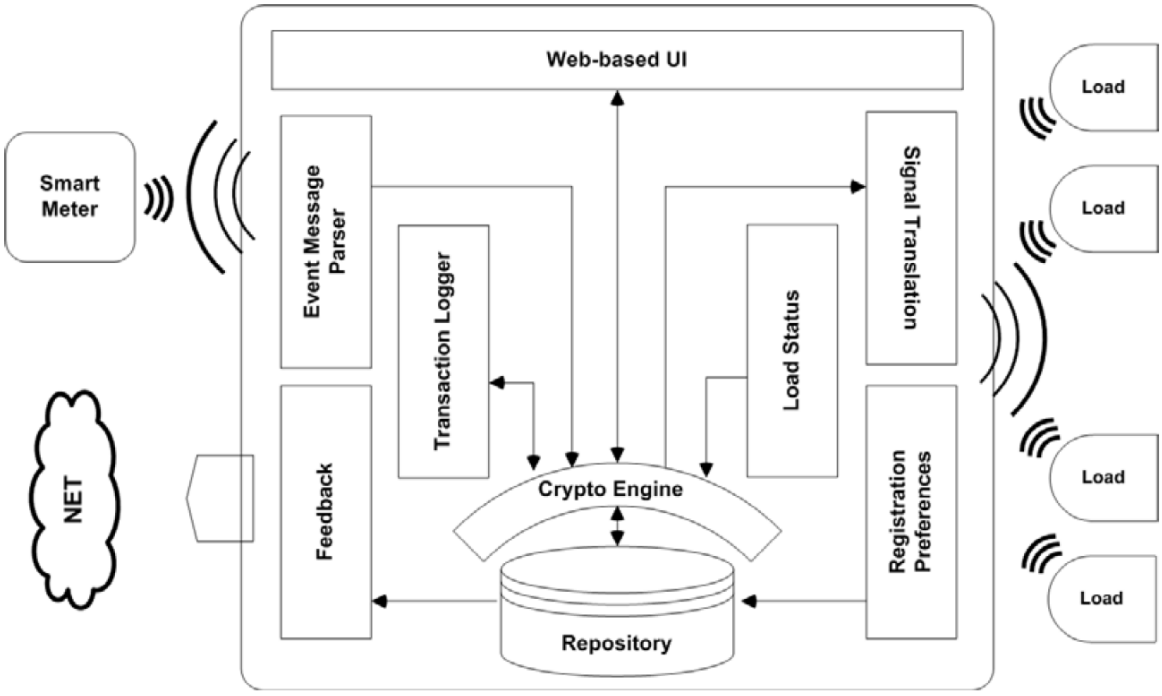


Figure 57: Service Gateway Architecture

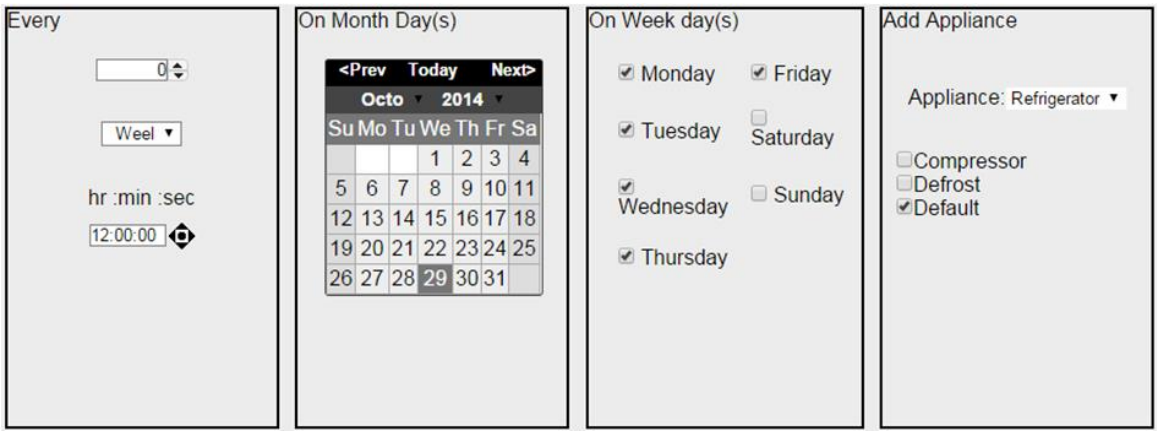


Figure 58: Web Interface to the Consumer Preference Engine

In Figure 58, a user can choose to curtail the function of the refrigerator's compressor, without affecting other functionality. Once an appliance is selected, the user can create a schedule that indicates when the appliance is available for curtailment; users can select the month, day of the week, and/or hour, and set the duration for how long the appliance can curtail during that time. The in-home gateway stores the preferences within the database, using a similar format to the UNIX job scheduler Cron.

Minute	Hour	Day of Month	Month	Day of Week	Duration (in minutes)	Appliance	Component to Curtail
0	12	*	*	1-5	240	Refrigerator	Any/All

Figure 59: Sample preference setting

The figure above shows a sample entry in the database, which states that for any weekday (Monday to Friday) starting at noon, the refrigerator is available to be curtailed for the next four hours.

Load/Appliance Controller

The appliance controller comprises a controller and relay. The figure below shows these devices connected to and configured for controlling an LED light.



Figure 60: LED Light

The appliance controller communicates with the in-home smart gateway and sends appliance control signals to the relay. Its design is similar to the gateway, containing a single board computer with a real-time clock, Wi-Fi, and ZigBee dongle. The appliance controller's enclosure includes an Ethernet port and a power connector. The figure below shows a schematic of the controller.

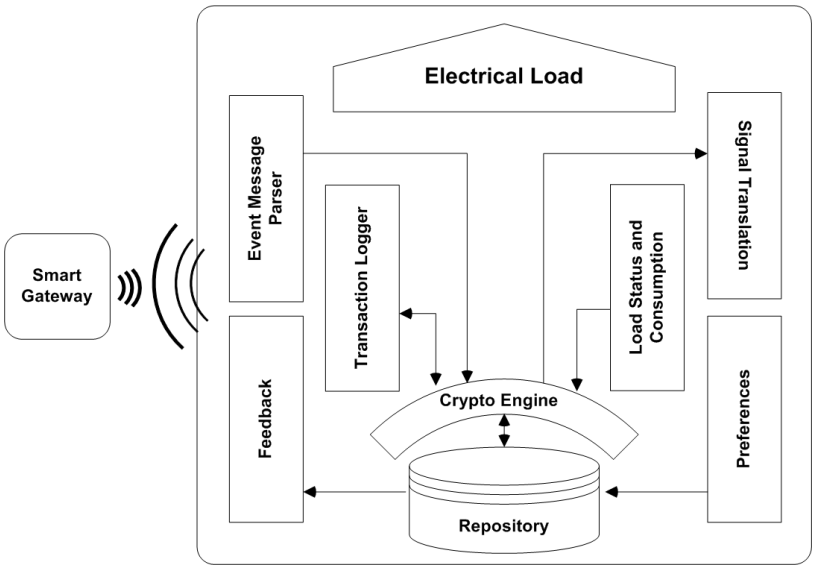


Figure 61: Controller

Results

Appliance controller was implemented to communicate with and control the internal operations of a refrigerator and dryer, and connect a battery management system to provide energy services for a local power grid. This section described the experimental setup for each device and how the appliance controllers affected their internal functions.

Refrigerator Implementation:



Figure 62: Refrigerator with appliance controller

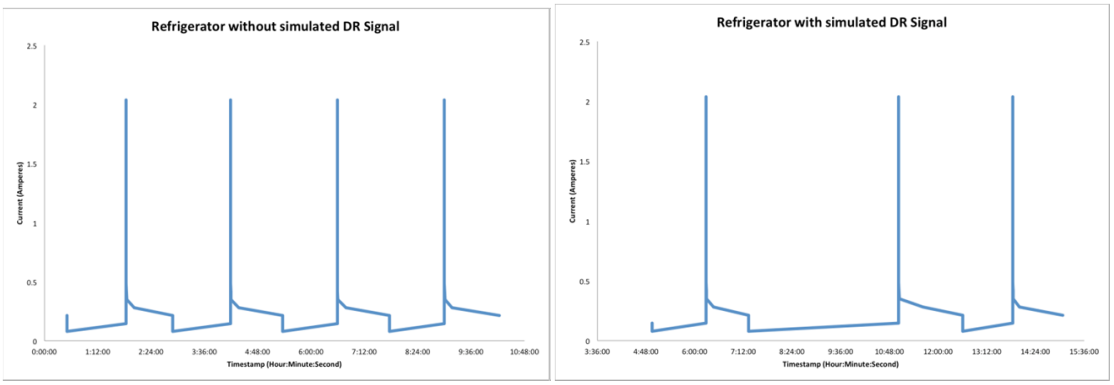


Figure 63: Refrigerator with and without simulated DR signal

Dryer Implementation:



Figure 64: Dryer with an appliance controller

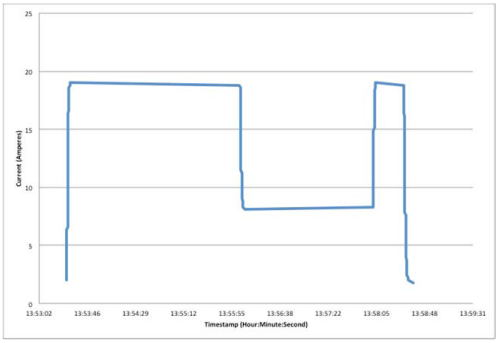


Figure 65: Dryer curtailment after receiving DR signal

HAN, along with the smart gateway and appliance controllers, was successfully tested for reliability and payload packet designs for the past 15 months. A refrigerator with an appliance controller under the control of the smart gateway was successfully operated for the past 10 months in graduate apartments of the UCLA DR test bed. The response of the refrigerator to simulated DR events was being tested and the multi-state load curtailment was consistent.

Obstacles and solutions

Demonstration of the technologies and process logic had some impediments and handicaps. Some of the key obstacles and solutions employed to overcome them are as summarized below:

a. Smart gateways used to breakdown randomly. On analysis, it was found that the gateways failed at some locations in the test bed when the room temperature used to rise over 75^{o} F. This was due to the high temperature (~95^{o} F) inside the gateway enclosure. This was solved by adding a heat sink and a fan in the enclosure.

b. WiFi communication used to fail quite often between the gateway and the access point as well as the control units and the gateway. The problem persisted even with dongles from four very popular vendors. The problem persisted even after trying out different range testing and direct line-of-sight deployments. Based on the WiFi user community observations, it was surmised that this problem might have been interoperability issues where the WiFi drivers might not fully comply with the specifications. This issue was solved by developing an intelligent communication monitoring module that automatically re-establishes the communication by running the link routine(s).

c. On observing some of the failures as described above, it was decided to develop an auto-reboot module in the embedded system. This was a configurable module which could be set to execute at a set time. Most of the control units and the gateways deployed reboot during midnight when everything reinitializes. This will preempt any problems that accumulate due to shortcomings in the embedded system, hardware drivers, or network connectivity.

d. Important operational hurdles in recruiting and retaining participants for the demonstration in the test bed. Dwelling units in the test bed are rental apartments, as a result there were tenant turnovers. Every turnover had hand-holding cost, where the tenant was to be introduced to the study and explained the concept of demand response. On understanding demand response some of the participants dropped from the study. In the case of those who continued with the study, there was the problem of maintaining WiFi connectivity. Site survey was required for each apartment as the interior layout would sometimes obscure the WiFi signals between the access point and the gateway, or the positioning of the appliance from the access point would weaken the signal strength. Another unforeseen problem was when some tenants would switch off power to the access point when they leave the apartment. The last problem was difficult to solve as the tenants repeatedly forgot about the need to keep the access point powered on.

Observations

During this project, the DR team collected the thermostat data only. However, UCLA installed smart appliances at their dormitories and the DR team collected smart appliances data.

For the thermostat data, the following figures were a sample of five different thermostats undergoing 24 DR events on August 30, 2014. It could be seen that during the DR event the thermostat settings were reconfigured and the temperature was following the new settings:

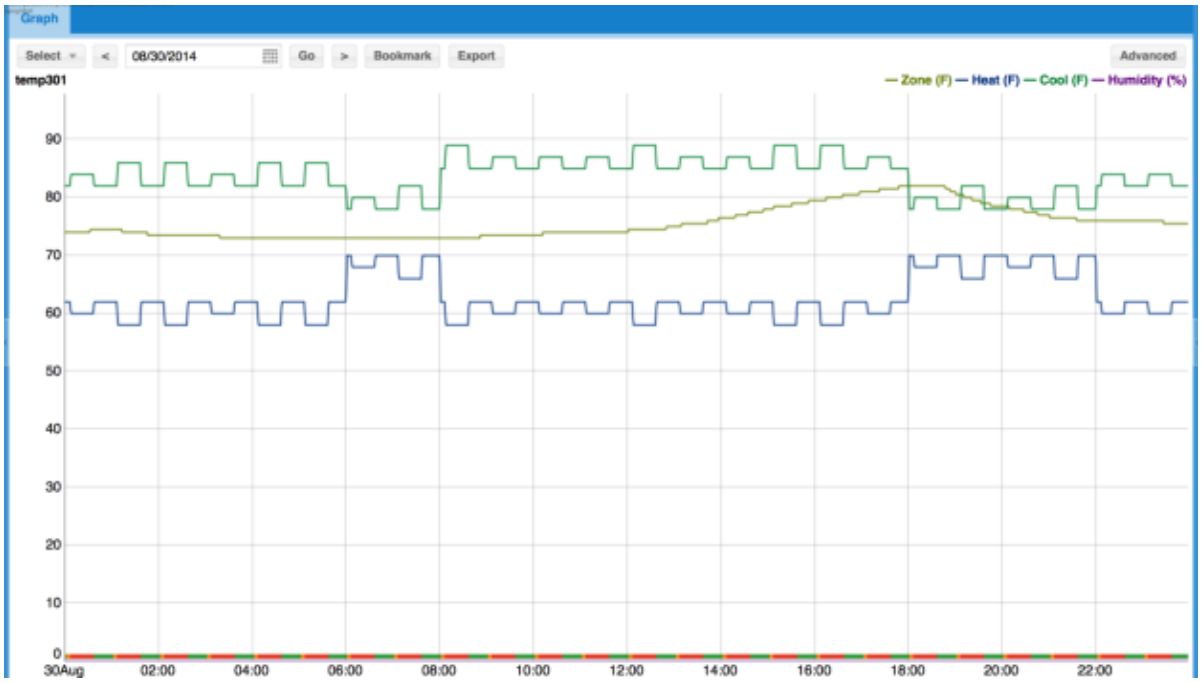


Figure 66: Thermostat "temp301" Temperature Graph for DR Event on 30 Aug 2014

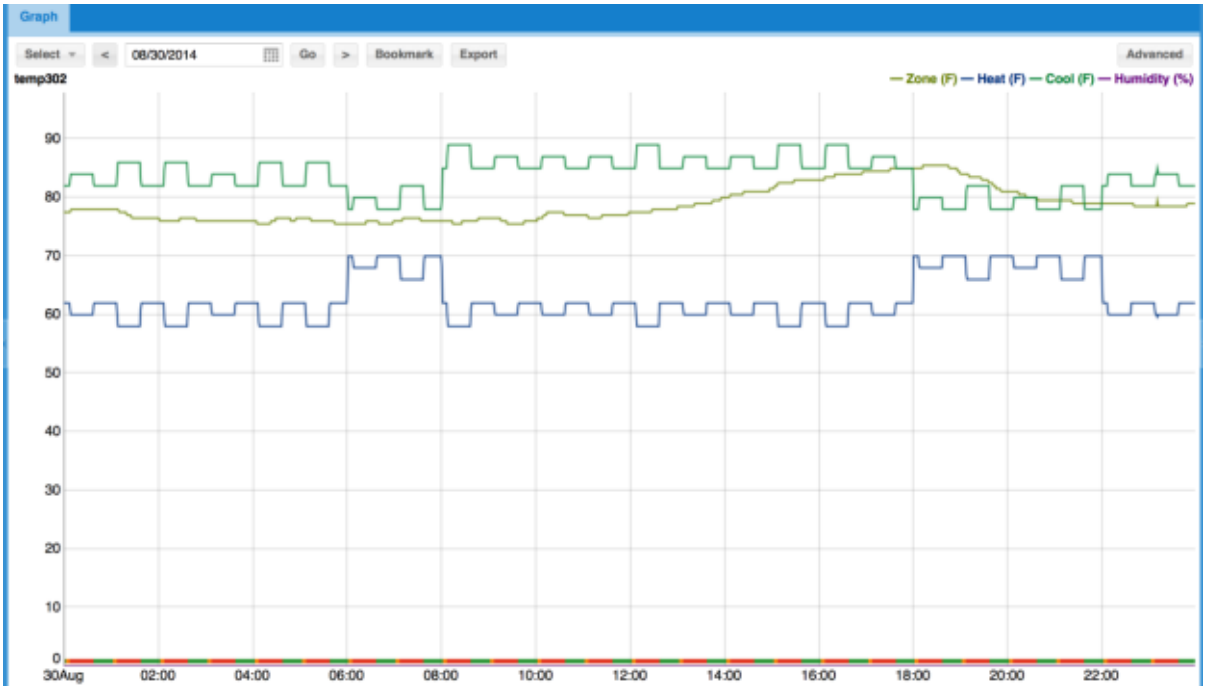


Figure 67: Thermostat "temp301" Temperature Graph for DR Event on 30 Aug 2014



Figure 68: Thermostat “temp303” Temperature Graph for DR Event on 30 Aug 2014



Figure 69: Thermostat "temp304" Temperature Graph for DR Event on 30 Aug 2014



Figure 70: Thermostat "temp305" Temperature Graph for DR Event on 30 Aug 2014

Lessons learned and future work

The project validated the role of HAN in residential demand response. The control units developed through this project proved robust and reliable. With the OpenADR client hosted natively on the control units, it was possible to execute DR events with negligible user intervention. Choice of WiFi network and

communication proved very pragmatic and served exceedingly well the variety of types of deployments in the test bed.

The technology could be extended with minimal adaptation to scale. The deployments can be segregated into aggregated units (building level, multi-building levels, gated community, etc.). The user participation and retention probably can be improved by designing an incentive system that would include supply of no cost automation hardware to the user and utility bill discounts for participating in DR events.

8.2.6 Large commercial customer participating in DR program: USC Campus Demonstrating B2G Technologies

The Demand Response Program demonstrated Building to Grid (B2G) concepts within the USC campus demonstration environment. B2G describes the interaction of the electrical grid with commercial buildings and aligns the end-uses of the building (heating, cooling, lighting, process loads, etc.) to the energy source (electricity, natural gas) serving the end-use. Activities associated with B2G include participation in demand response, diagnostic and energy efficiency analysis within the building itself and demand response testing to optimize load reduction and minimize building occupant negative impacts.

The USC facilities include a range of user infrastructures: Commercial, medical, retail, semi-industrial, and residential which will be used for this demonstration. This will provide LADWP with outcomes and performance data for deploying fully-integrated DR Smart Grid operations and technologies for all customer types. The demonstration outcomes and data can then be used by LADWP for full scale deployment; for developing the business case and for selecting the best operational models and technologies.

Methodology

To demonstrate and meet the success criteria for this demonstration, the Demand Response team leveraged existing sensors and the building management system at USC campus, installed metering to address specific end-use loads, and developed a series of demand response strategies to be tested with the varies building types on campus. The historical and real-time AMI and System data for demand-side load management decisions was used for DR control purposes and also with load forecasting and DR optimization features available from DDS, optimal and reliable DR events was conducted and demonstrated at the USC campus. The Control center at USC received commands from LADWP, and communicated with DDS to apply the DR strategy on USC buildings. For this purpose, different dashboard and database, archiving, and control modules were designed and integrated. Different strategies for DR were tested, different building types and schemes were tested, different days and weather conditions were tested and the results from end use load usage and curtailment profiles, and power quality perspective were demonstrated.

Three primary demand response strategies were employed for the demonstration project as outlined below:

Global Temperature Reset: The temperature set point of the space is increased; the thermostat compares the space temperature to the reset temperature, and if it is higher, sends a signal to HVAC system. If the HVAC system is a variable air volume system, the VAV box will reduce the amount of air flow to the space,

thereby reducing the fan motor energy. If the HVAC system is a constant volume system, the cooling coil valve will close slightly, reducing the amount of chilled water required from the chilled water system.

Variable Speed Drive Reset: The speed of the fan is slowed down, resulting in a reduction in motor energy.

Equipment Duty Cycling: The piece of equipment is shut off for a time period. Duty cycling of fans is performed when a variable speed drive is not available on an air handling unit. Typically, these are smaller fans which serve a suite or small area of a building.

Technologies Deployed

The existing USC Building Management System (BMS) and USC electrical metering system was used as the foundation for development of the USC Demand Response system to interface with LADWP and the DDS. Multiple Tridium JACE systems and associated programming were established to receive and automate the Automated Demand Response process working in conjunction with the building management system. Building level programming was performed to develop the demand response strategies to be invoked during a DR event. A single dashboard was developed to enable a single point of communication and building selection for a demand response event with additional dashboards for interconnecting entities to review data receipt. A third-party energy reporting representation referred to as the dashboard was established with Lucid and several visual dashboards have been established around the USC Campus. An Eaton Gen64 system was established to provide faster energy reporting communication to the DDS and for reporting back to DWP.

Standard ADR and EMS communication protocol were adopted, namely ADR 1.0, and BACnet™, and translational interfaces of REST and OBEX for communication between independent systems.

Success Criteria

The success criteria for this use case are in the demonstration and documentation of the following:

- The installation of sub-metering in various building on USC campus to demonstrate the end-use load profile for HVAC fans, cooling system, lighting, and other end-uses
- Develop a series of demand response strategies to provide a sustained load curtailment
- Demonstrate reliable, and repeatable automated demand response operations
- DR testing was conducted and operations optimized to provide the greatest sustainable load curtailment with less than 15% of occupant complaints.

Observations & Results

Occupant Impacts and DR Strategy Optimization

For the demand response strategies used, occupant discomfort during an event could be reduced through optimization of the set points used. Figure 71 showed the Occupant Comfort calls from October 2013 to May 2016 with 11% of the calls attributed to the Demand Response Event. When the testing at USC first started, an aggressive VFD reset speed to 30% was used. We found this setting was too low and in December 2014, a global change to a minimum speed of 50% was established. This resulted in a dramatic

reduction in DR related comfort calls showing that 4.2% of the comfort compliant calls were associated with the DR event.

Month	Number of Events	Total Number of Buildings Tested	Total DR Related Calls	Total Hot Calls 1-6PM All DR Buildings	Percent of DR Calls to Total Calls	
Oct-13	4	144	12	29	41.4%	
Nov-13	7	176	4	23	17.4%	
Dec-13	3	60	4	26	15.4%	
Jan-14	10	23	6	28	21.4%	
Feb-14	10	30	2	32	6.3%	
Mar-14	7	1	0	24	0.0%	
Apr-14	2	36	8	22	36.4%	
May-14	6	106	4	30	13.3%	
Jul-14	1	11	2	36	5.6%	
Aug-14	3	25	3	36	8.3%	
Sep-14	7	139	20	82	24.4%	
Oct-14	6	71	8	40	20.0%	
Nov-14	14	132	10	37	27.0%	
Dec-14	2	41	1	13	7.7%	
Jan-15	1	17	1	28	3.6%	
Feb-15	1	31	1	19	5.3%	
Mar-15	1	39	1	30	3.3%	
Apr-15	1	25	0	28	0.0%	
Jul-15	1	18	0	29	0.0%	
Aug-15	2	37	3	59	5.1%	
Sep-15	1	30	4	26	15.4%	
Oct-15	1	26	3	37	8.1%	
Dec-15	1	10	0	14	0.0%	
Mar-16	1	10	1	21	4.8%	
Apr-16	6	47	3	28	10.7%	
May-16	7	52	2	13	15.4%	

Number of Events	Total Number of Buildings Tested	Total DR Related Calls	Total Hot Calls 1-6PM All DR Buildings	Average DR calls to Total Calls	Avg After Dec-14 Change
106	1337	103	948	10.9%	4.2%

Figure 71: Occupant Comfort calls

End-Use Electrical Load Profiles

Obtaining electrical load profiles which could clearly be designated to only one end-use was very difficult. As buildings were remodeled, loads were connected to the electrical system as needed, making it essentially impossible to separate out the loads clearly, without a significant cost. A focus on only those loads which could be influenced by demand response should be addressed, and often a grassroots engineering approach in estimating the impact could be as reliable as detailed end-use metering.

The end-use metering greatly assisted in identifying equipment which was not operating optimally, such as equipment cycling, so that those issues could be addressed.

Building Subsystem Interactions

To demonstrate the interaction between building sub-systems, the results from a Variable Frequency Drive (VFD) reset demand response strategy at Leavy Library building on December 9, 2015 2:15 PM to 3:40 PM are illustrated in Figures 72 and 73. A VFD DR strategy reduced the speed of the fan directly reducing the amount of energy used by the fans. Figure 72 illustrates screen capture of the direct load curtailment response of the reduced VFD setting. An abrupt and stable drop in fan energy electrical usage was achieved, of approximately 60 kW.

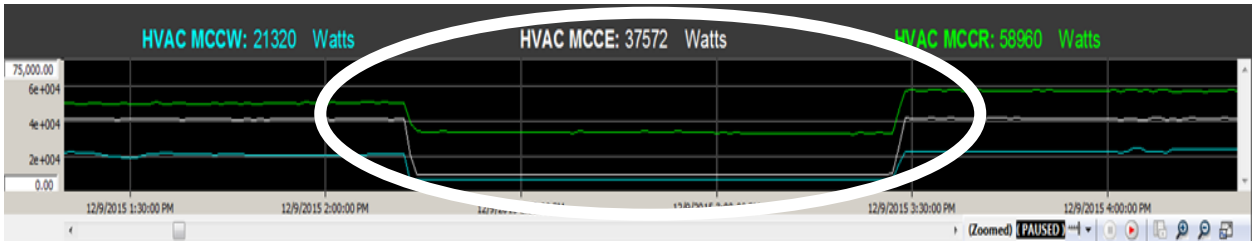


Figure 72: Leavy Library HVAC (Fan) Operation

As a result of the lower VFD setting on the fan the air flow was reduced. With this reduced air flow there is a reduction in the amount of cooling needed. This reduced chilled water load results in a reduction in chiller operation. Figure 73 illustrates the reduction in chilled water electrical usage during the DR event.

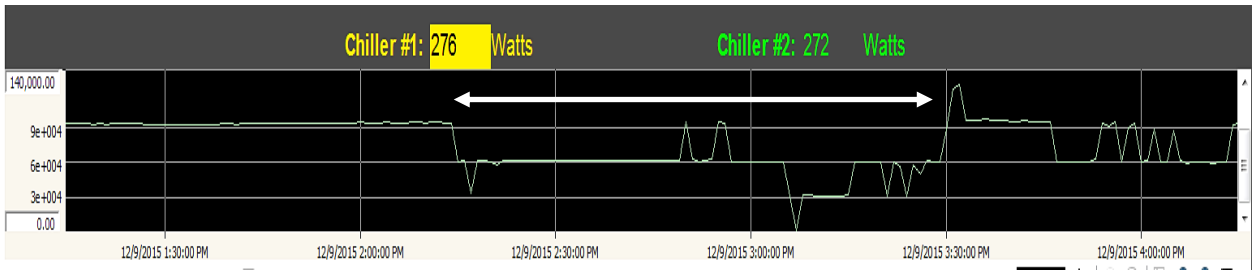


Figure 73: Leavy Library Chiller Electrical Load Profile

Measurement Density

The impact of measurement density for demand response specifically addressed the amount of data available at a room (zone) level and how that data impacts load curtailment. The test scenario compared the use of a global temperature reset (GTR) strategy, where control and data was available at the zone level, to the VFD reset for a building without zone level control or data. Figure 74 illustrates that VFD reset provides a consistently higher level of load curtailment impact as compared to GTR.

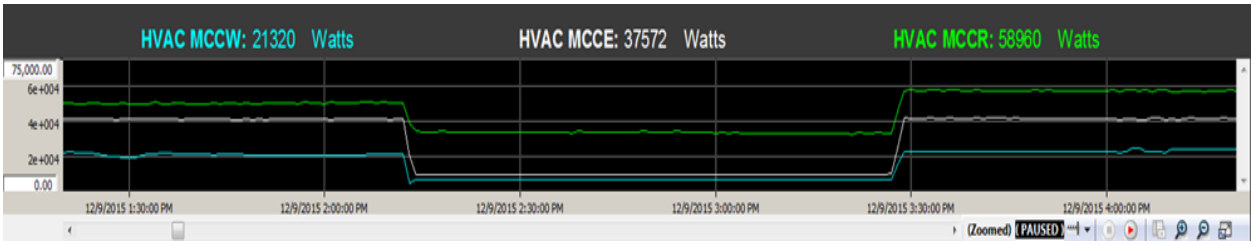


Figure 74: VFD Reset

In assessing space comfort conditions during a demand response event, either individual room space temperature data, or aggregated return air temperature is used. The use of individual space temperature data resulted in the system opting out of the demand response event earlier than use of return air temperature. A higher density measurement did not result in a higher level of demand reduction, and dependent upon how the data is used, can result in a lower demand response reduction, although a potentially higher customer dissatisfaction rate.

Air handler information such as return air temperature can provide a reasonable proxy for discrete zone level information, albeit, it will not reflect the extreme conditions. To accommodate potential outliers, the limits on the return air temperature are lowered (maximum return air temperature before remediation strategies are put into place).

Demand Response Strategy Optimization

The VFD reset strategy (either alone or with Global Temperature Reset) has, on average, provided the greatest Watt per sq. ft. impact as compared to the other strategies. Figure 75 illustrates the overall electrical impact for each building, by strategy by month. Note that the impact of demand response during cool months (Oct, Nov., Dec.) are minimal, since the demand on cooling and air flow are already low and a DR impact is negligible. Demand response impact for June through August are also reduced, since the campus is in summer session, which has a much lower usage and therefore the systems are not operating at full load prior to the demand response event. For buildings and facilities which do not have a “reduced operational season”, it is anticipated that similar results as April, May, and September would occur during the cooling season. When school is in full session (April, May, and Sept) and in cooling mode, the demand response creates impacts by an average 1.4 w/ sq. ft.

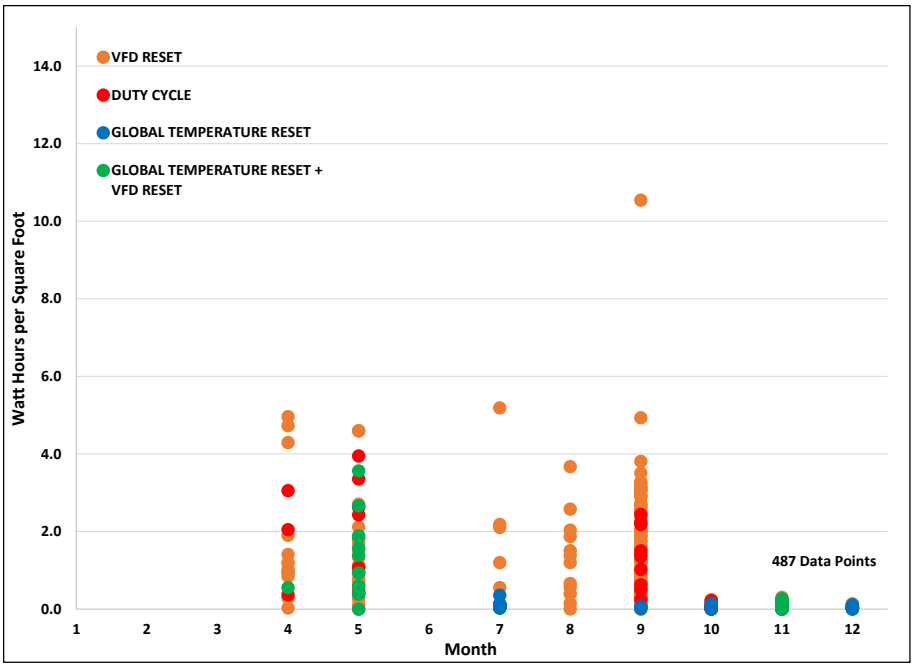


Figure 75: Demand Response Strategies versus Electrical Impact (W/sq. ft.) by Month for All Buildings

Demand Response Power Quality Impacts

The demand response strategies used in this program abruptly change the operation of rotating equipment which has called into question whether power quality is negatively impacted. Analysis of the power factor at the buildings level and at a feeder level on which multiple buildings were in demand response indicate that the changes made in the building to invoke the demand response did not have a negative impact on power factor and therefore power quality.

Figure 76 indicates that the power factor during a DR event is not unlike that during a non DR time period.

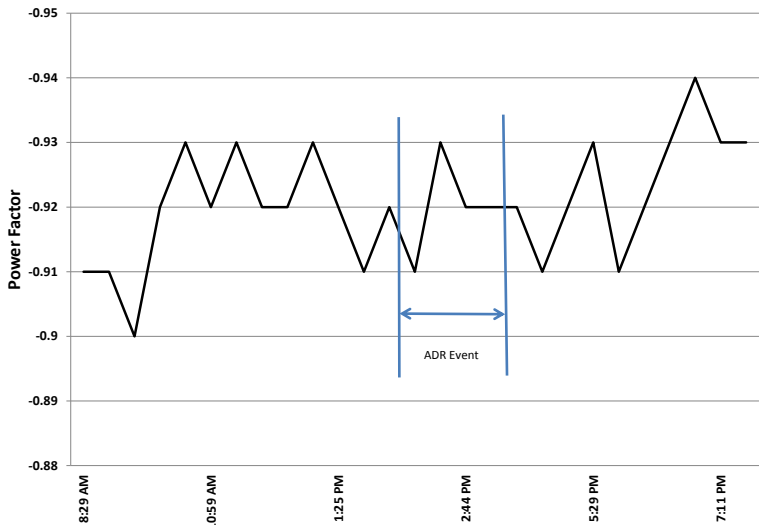


Figure 76: Power Factor Profile for Duty Cycling Building including a DR Event

The impact of demand response in several buildings on the power quality of an electrical feeder was evaluated. Sixty percent (60%) of the buildings on the given electrical feeder (Jefferson vault Feeder Q) were engaged in demand response at the same time. Figure 77 illustrates that the power factor during the DR event did not vary any greater than without the DR event.

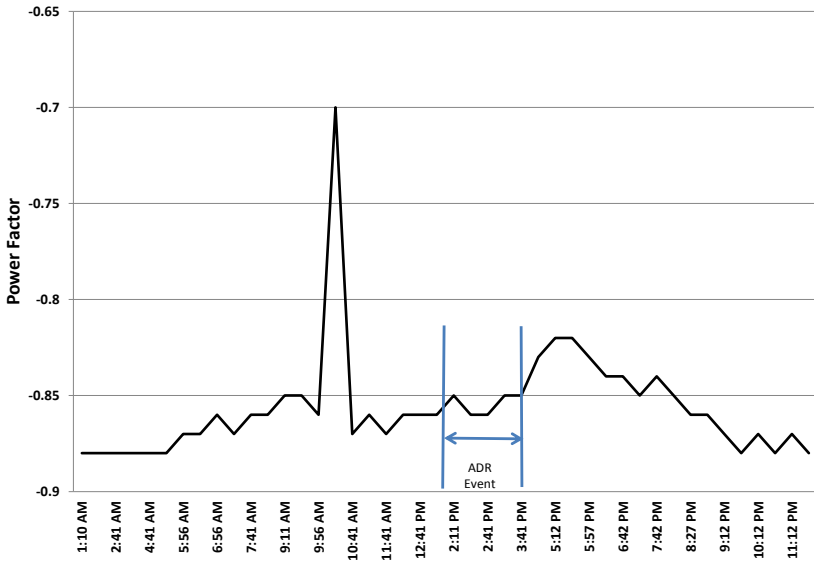


Figure 77: Feeder Q Power Factor Profile Including a DR Event

Based on the metering and reporting, there does not appear to be an impact on the power factor at the building or feeder level for the demand response strategies used in this project.

Demand Response Economics

The University has a significant energy management system based on direct digital controls and an energy control center which consolidates building information which enables remote monitoring and control. Each major piece of equipment can be scheduled on/off and operating parameters can be adjusted to meet the space needs. The cost to invoke demand response strategies, given this infrastructure, are programming and commissioning (essentially no little additional hardware is required). It is with this understanding that the costs for performing the programming for *only* the demand response strategy for a building (excludes automated communication with DWP and VSoE DDS, electrical metering and any additional supporting systems) are presented in Figure 78.

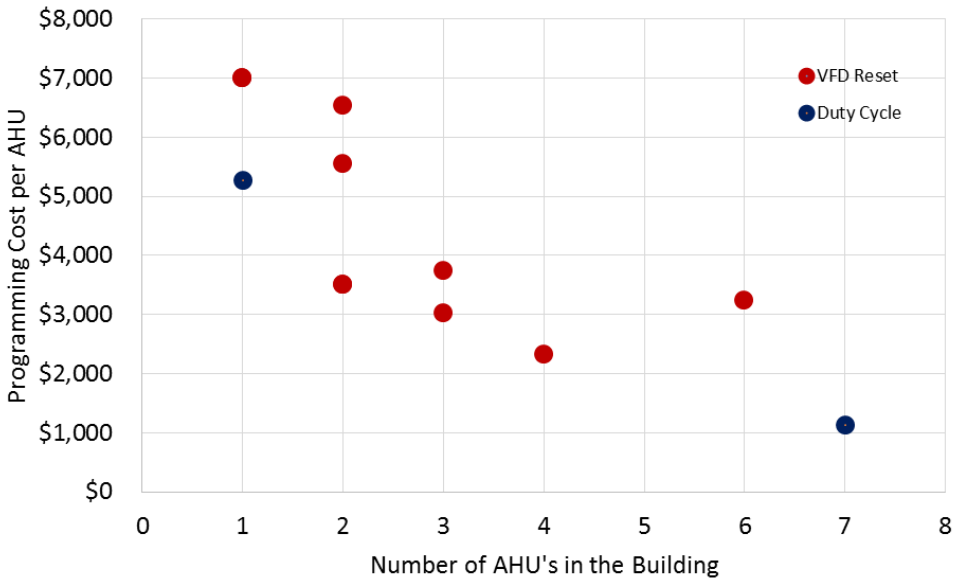


Figure 78: Demand Response Strategy Programming Costs

Dynamic Building Operations

It is critical to appreciate the impact of system upgrades, building renovations, and operational disruptions when overlaying a program (such as a demand response) on an existing infrastructure. The existing USC metering system was not intended to provide detailed 15 minute data at a rate needed for this project. Construction on the campus interrupted communication between systems such that back-up strategies were needed to ensure system operations. Renovation within buildings would remove buildings from DR consideration and would require re-programming of DR strategies when brought back on line. Upgrades to the existing building management system required re-mapping of points. The building management system is used by a range of individuals from front line technicians solving hot and cold call issues, to the detailed programming of control logic. Therefore, continuous testing of the system was necessary to ensure functionality, since changes are being made continuously to the system.

The summary of accomplishments in this demonstration is listed below:

- Identification of end-uses and quantification of demand response potential for commercial buildings
- 49 buildings enrolled into the SGADR covering a total of 3,658,400 sq. ft. of various purposes building space.
- Development of 6 DR strategies, programmed, tested and deployed throughout the campus
- Developed a building level dashboard for each building in the DR program to monitor, control and report building operations, enabling individual air handling unit opt-in and opt-out capabilities.
- Developed a Summary dashboard to monitor, report, and track the overall demand response event
- A dashboard to track hourly curtailment and strategies by building.
- Successfully achieved the 1.2 MW/hr. curtailment goal.

- Installed Triduim Jace equipment and programming software to handle the balance of DR system communication and control and a regiment for building equipment operational testing and verification for optimum performance of ADR events occurs regularly
- Successful automated DR communication from DWP to USC's buildings and estimates and achieved values communicated back to LADWP from the DDS Policy Engine for the entire event and by building.
- Migrated from FTP communication to Eaton Gen64 Flat Files for faster, nearly instant energy reading transmission.
- Based on the metering and reporting performed during this program there does not appear to be an impact on the power factor at the building or feeder level for the demand response strategies used in this project.
- Monthly testing and storyboards were completed for 21 months.
- Successful Automated DR presentations to Department of Energy on several occasions
- Building occupant complaints associated with DR testing were reduced to less than 5% of the hot/cold calls received over the demand response period.
- Submitted reports that include the Building Audit Report, Building to Grid Report, Final Report and Final Technical Report

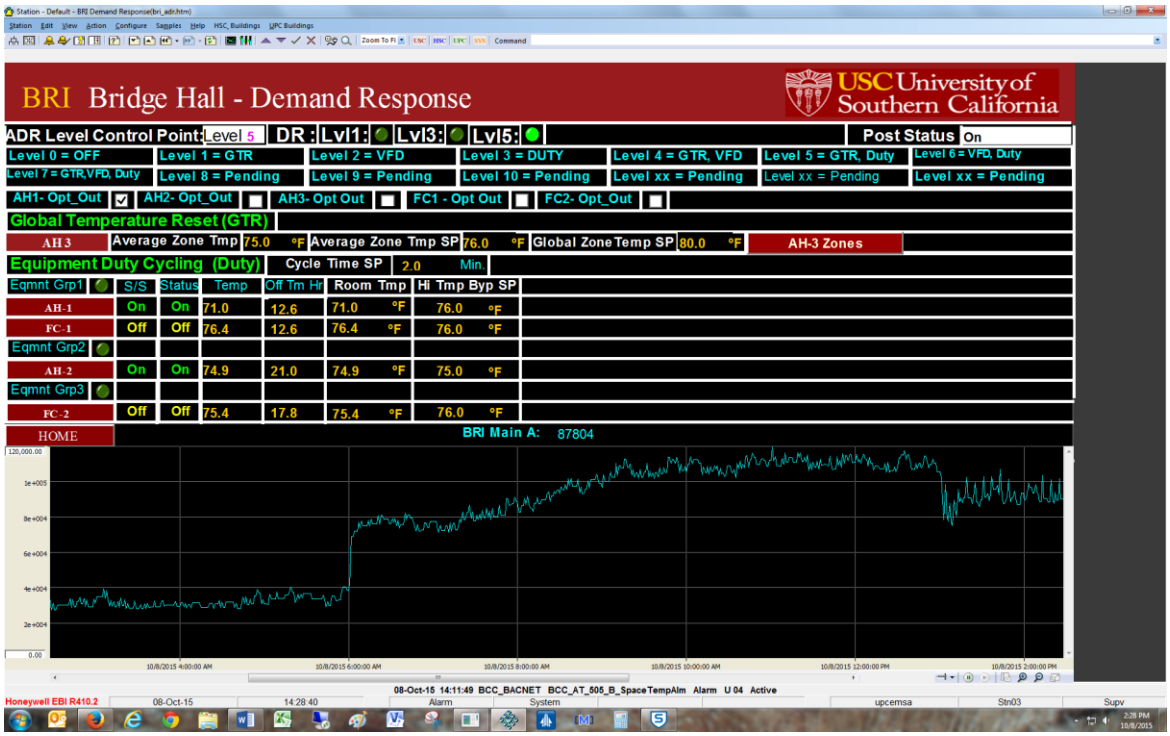


Figure 79: USC-EBI: Building BRI Demand Response shows energy trend curtailment during event

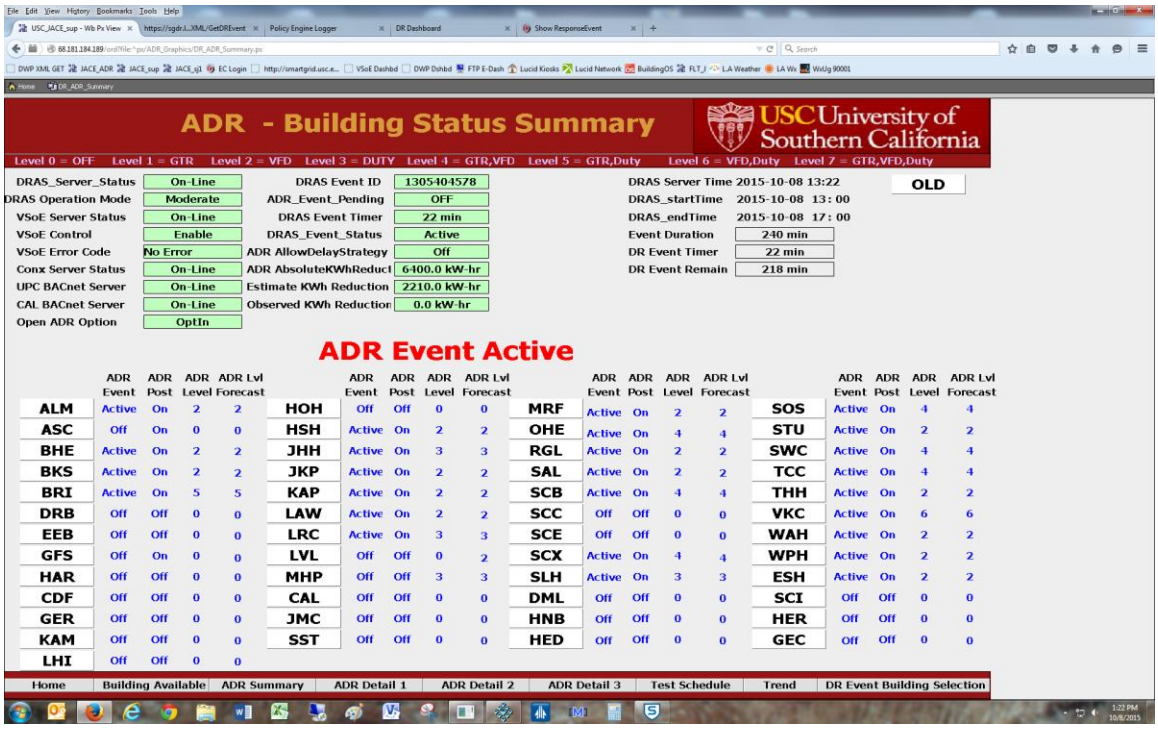


Figure 80: JACE Supervisory dashboard – Active Event

The initial report for building selection will then look like the figure below:

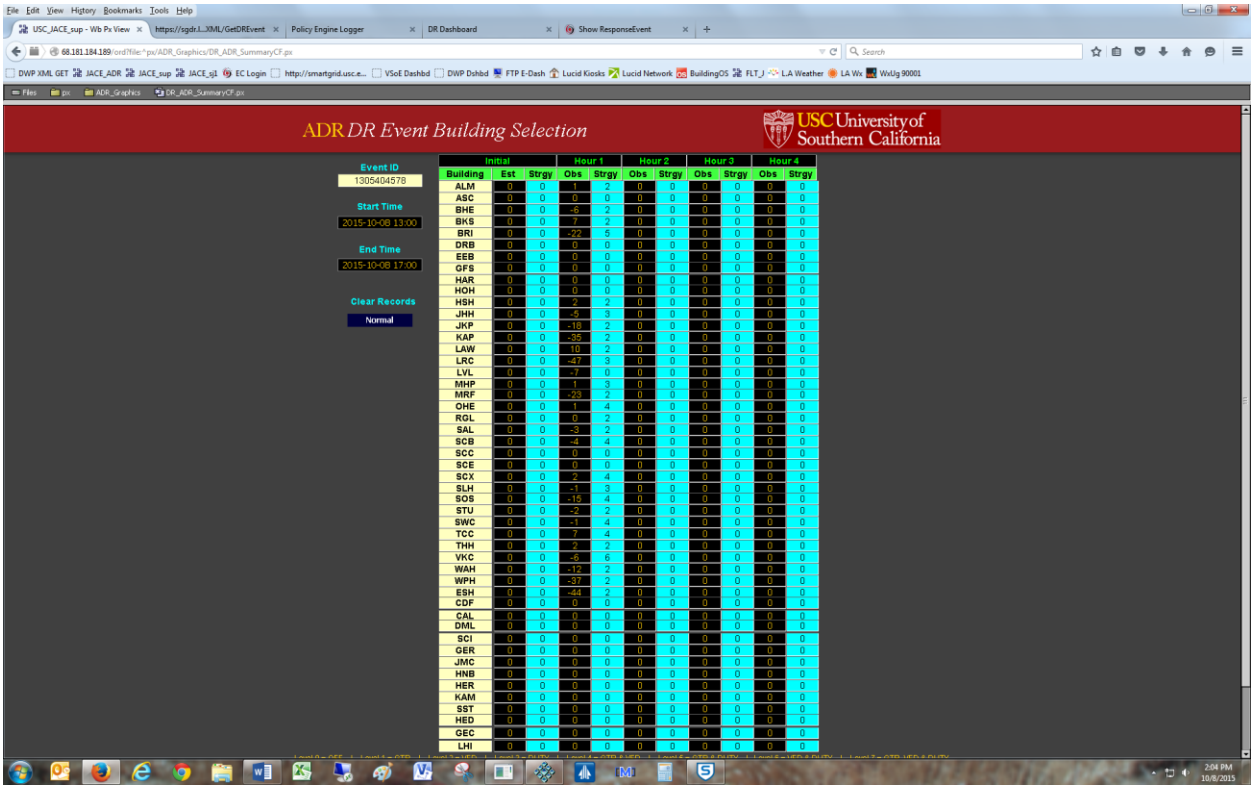


Figure 81: DR Building Selection summary indicates strategy and reductions for each hour

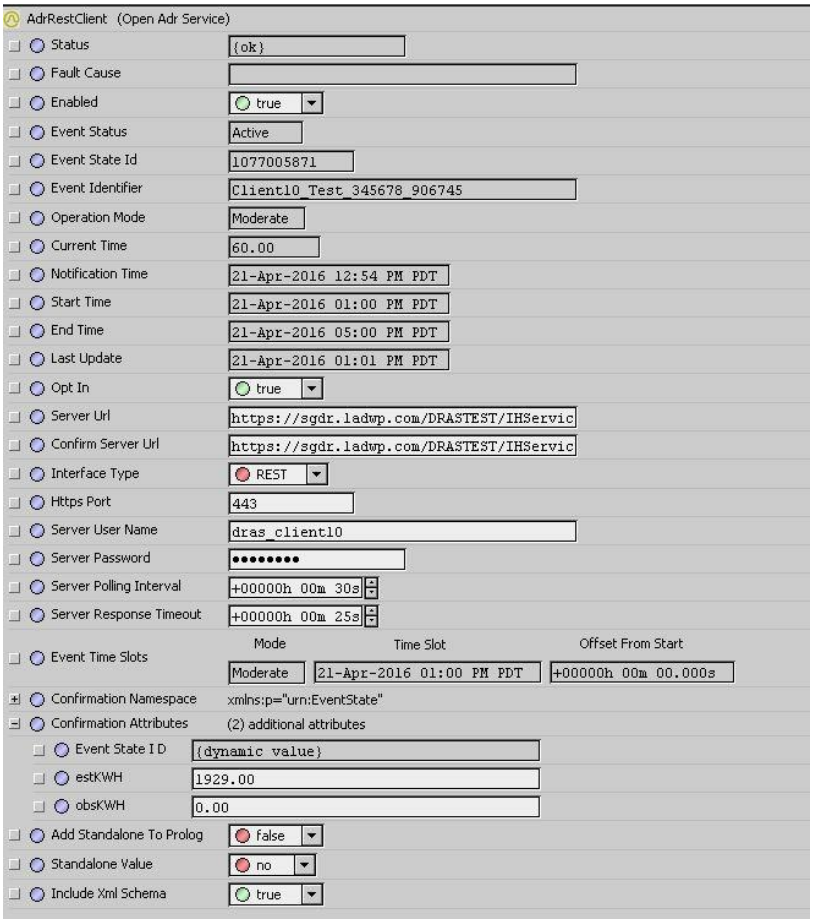


Figure 82: ADR Jace Communication with LADWP DR Server

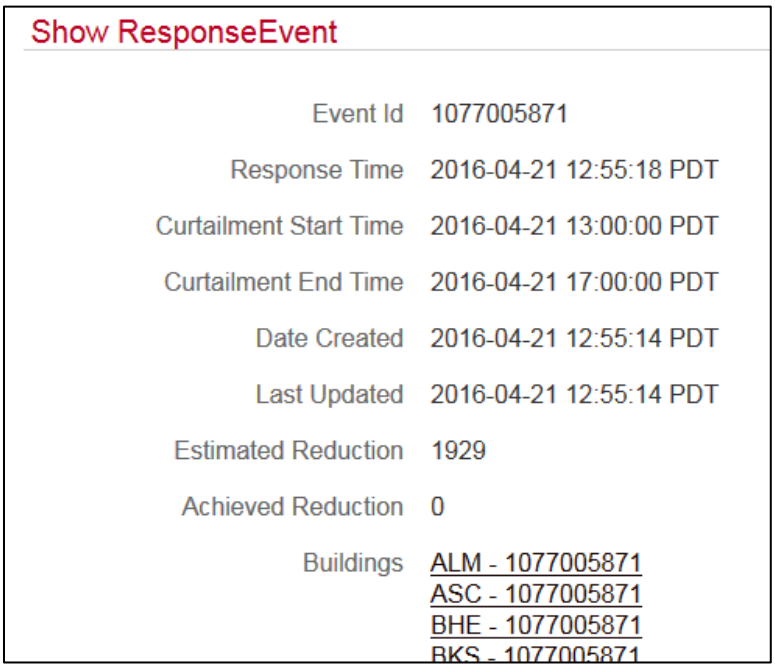


Figure 83: Energy Connexx (Response from VSoE)

8.3 Problems Encountered

Risk_Title	Risk Description	Likelihood of Occurrence	Cost Schedule Impact	Risk Consequence	Risk_Mitigation
Technical	MDM systems back-end integration, validation and commissioning. Additionally, MDM may be unable to collect the data once every 15 m for real-time DR events.	Low	Low	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns • Failure of MDM integration will lead to system failure of DR Data Repository and DR Decision Support • Unable to perform DR analysis during "DR Event"	DR has developed a plan and support team to work on realizing functionality, read time has been reduced but still not at 15 min intervals.
Stakeholder	A certain number of customers are required to enroll with DR. Failure of demonstrating DR Use cases with insufficient number of customers. Web Portal is delayed.	Low	Low	Failure of demonstrating DR Use cases	Increase participation and enrollment in the DR programs with community outreach and education. Understanding the direct benefits of DR may help boost customer participation. Did have not enough time to complete demonstrations with portal.

Technical	Issues with CIS systems back-end integration, validation and commissioning	Low	Low	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns • Failure of CIS integration will lead to system failure of DR Data Repository, DR Decision Support, and STI	Work with the responsible parties to clear constraints and bottlenecks. Help facilitate the process. Raise concern level and escalate as needed. Fixed defect in CC&B.
Technical	Identifying SGRDP customers in CC&B.	Med	Med	• Failure of demonstrating DR Use cases	Meters were uploaded into CC&B inventory, also configurations and templates were created for each type.
Schedule	SGRDP DR Servers have overheated and been down for two weeks	High	Low	Delay of DR Schedule	DataPower is up, network firewall rules need to be setup, fixed yesterday 2/4/2014
Staffing	CB Web Portal design has a hard limit at 52,000, any additional customers will not be able to sign-up and participate.	Low	Med	Limited data and customer participation.	Brought in new vendor for web portal, design specs have changed.
Technical	MDM data collection has been delayed due to issues with data collection and Data Repository.	High	High	Web Portal delays may impact customer sign-up and participation for both CB and DR studies. Further delay will impact data collection period and quality of demonstrations. Customer dissatisfaction may lead to negative Smart Grid publicity, financial claims, legal issues.	AMI / DR team working with MDM to update with all historic data.
Technical	CS may be unable to monitor DR, EV, and CB systems due to issues with SNARE	Med	High	Impact scope.	CS team is working with DR to install SNARE system. SNARE installation complete with EV. SNARE is replaced by

					rSYSLOG - resolved for CB.
Technical	Performance issue is impacting CB web portal. ITS advised resource is not committing time resource on project.	Med	Med	Would cause a schedule delay.	Four servers moved to new environment. Clean-up completed
Schedule	Poor return of registration - cannot meet the project number of acceptance for planned demonstration	High	Low	Will have to be abandoned due to lack of time remaining on project. Output of demonstration may not be a sizeable representation of service area.	Closed DR-CB3-1 use case / Demo.
Technical	Peak test did not work in PD which will impact DR residential demonstrations	High	High	Unable to complete DR residential demonstrations as designed	Trace the traffic to identify where the block is. Peak test successfully.
Technical	MDM sync w/ CC&B Performed a MDM sync resulted in more than 100 errors, corrected errors, but sync errored out.	High	Low	Unable to sync MDM errors/uptime to Data Repository	Reached out to Oracle to mitigate. On-hold as this is not priority for team right now since they are still working on Settlement.

Table 58: Problems Encountered in DR Demonstrations

8.4 Lessons Learned

The major lessons learned in DR include the following:

- Installation and commissioning should be intelligible for every customer to promote installation by end-users rather than by professionals to keep the cost down
- There is a dearth of electrical load control units that are fully compatible with utility, customer and technology platform requirements
- Interoperability of the load control nodes should be investigated prior to deployment
- Home Area Network should be plug-n-play to support the load control nodes incrementally at the convenience of the end-user
- Site survey tools would be required for wireless range and connectivity tests

- Failsafe meshing operations should be an inbuilt feature of the network because of the dynamic nature of the end-use environment where wireless radio operations can be impacted
- Messaging, alerts and notifications should be lucid and appropriate for the different actors.
- Recommend to have a consistent (potentially curated by a dedicated administrator) MDM historian that can provide clean data to the DR engine
- Ensure algorithms are developed and tested for scalability and near real-time performance. If performance improvements are required, then parallelization technical and more advanced hardware can be utilized to speed up processing
- For software integration, it's essential to adapt DDS to be compatible with FMS despite changes and software should be adapted according to changing requirements
- A good API (includes a set of function definitions and protocols, and software tools to be used for building and linking software components. makes it easier to develop a program as it provides all the building blocks which are put together by the programmer or system architect. Therefore, it's important to establish an application programming interface (API).
- Develop a process by which changes to equipment, requirements, or software interfaces are reported to all integral parts.

8.5 Conclusion

Development of the DDS allowed the importation of historical and real-time data, such as AMI, CC&B and weather data, which enable forecasting load demand at the customer level, which led to a successful automated DR communication from DWP to USC's buildings and estimates and achieved values communicated back to LADWP from the DDS Policy Engine for the entire event and by building. The load forecast and generation capacity information could be used by the system operator to determine when there is going to be a peak load at a certain substation in a future time and load curtailment in order to avoid scenarios where demand exceeds the generation capacity, requiring the utility to buy extra power from the spot market at higher rates in order to avoid power outages and ensure grid reliability. Operators could use the feeder-level load forecast information to determine which feeders and subsets of customers connected to the feeders have good potential for load curtailment. Shifting demands away from peak hours add to the benefits of cost reduction by deferring building new, expensive peak generation facilities. DR effort in studying efficient selection of the best consumption prediction method provides flexibility to utility planners and operators to conduct either long term planning and day-ahead or hour ahead adjustments.

During periods of high energy demand, a small reduction in demand produces a relatively large reduction in the market price of electricity. Reduced demand can avoid rolling blackouts and reduction in energy costs. Accurate and efficient prediction of energy consumption is critical for a successful DR event. VSOE team monitored electrical usage for efficiency evaluations. Efficient selection of the best consumption prediction method allows utilities to optimize energy consumption during peak hours by applying various demand response techniques. By enabling demand response to be performed in a close to near-real time, the VSOE team developed technology that can facilitate the reduction of emission (societal benefit) by reducing the need for support of peak demand.

DR demonstrations supported greater flexibility by accommodating to new energy technologies, renewable, intermittent and distributed sources. New technologies such as renewable energy resources that are intermittent in nature are expected to introduce a lot of variability and uncertainty into the system, particularly if they are to be integrated in a distributed manner in a large scale (i.e., at the distribution network). The outcomes of the VSOE research facilitated the seamless integration of such new technologies, providing the flexibility to utility planners and operators to conduct either long term planning and day-ahead or hour ahead adjustments.

9 AMI Overview

9.1 Summary

The AMI project is one of the fundamental parts of the SGRDP, per agreement LADWP and DoE.

The scope of the SGRDP AMI project has been to install approximately 52,000 smart meters, the supporting communication network and back office applications and operations in order to support a Smart Grid system, as defined by Article XIII of the Energy Independence and Security Act of 2007 (EISA-2007).

For this project, 'smart meter' is defined a meter with the following fundamental capabilities:

1) Two-way remote communication between back-office and the meter
2) Recording usage data in interval (load profile) format
3) Capability to indicate more-than-billing data (e.g., power quality)

The AMI system, therefore, will include power meters- communicating over RF and cellular networks, demand meters, and EV meters which collect more-than-billing data.

Considering the DoE's desire to share lessons learned from Smart Grid projects with other utilities throughout the country, this section records the experience and lessons learned from the LADWP SGRDP AMI Project.

The SGRDP AMI project is intended to enable or accomplish the following objectives:

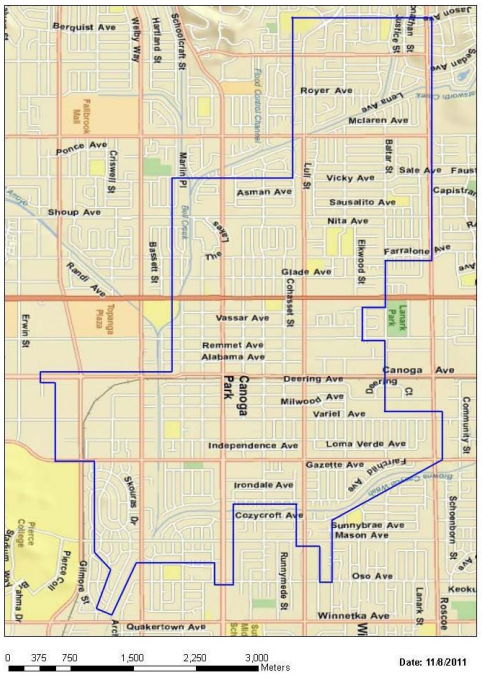
1) Provide means for LADWP to experience remote two-way communication with meters.
2) Provide means for LADWP to collect more-than-billing metering data, such as power quality and power monitoring.
3) Provide mechanism and basic data for carrying out 'demand response' events in order to provide load leveling and peak load shaving during critical peak load periods or whenever load reduction is deemed necessary.
4) Provide mechanism for managing the distributed energy resources (DER) such as solar photovoltaic data, in order to balance the grid in conditions where additional resources are needed to handle the load.
5) Provide mechanism to monitor Electric Vehicle (EV) charging and customized EV electric power billing in order to encourage earlier adoption of EVs and provide grid load management associated with EV charging.
6) Provide metering of power usage at various service connections to better understand energy consumption patterns and load profiles.
7) Enable the capability to provide customer-related usage information as well as timely feedback to the customer via a customer portal in order to encourage reduction of consumption.
8) More timely preparation of the power consumption bills which will support better energy management / conservation, and also improves the utility's revenue.

9) Enable improved power outage detection and management, by processing the Power Outage Notification (PON) and Power Restore Notification (PRN) received from meters at times of power outage and power restoration. Outage Management Systems (OMS) should be able to receive these notifications and create reports or tickets for field crews to respond.
10) Enable remote service connection and disconnection to manage move-outs, payment delinquencies, etc.

In light of the SGRDP's partnerships with USC and UCLA, the project included these universities' surrounding areas as part of smart meter deployment areas.

The following maps indicate the major areas of smart meter deployment:

Region 1



Region 2

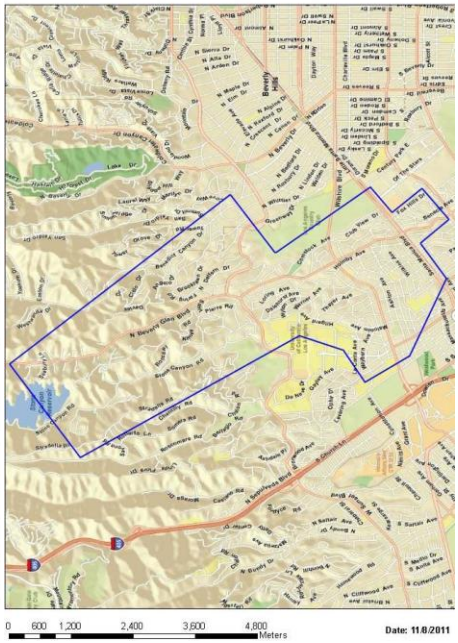




Figure 82: Major areas of smart meter deployment

The AMI Project includes four demonstration areas: metering system, communication network, back office (data collection), and the end-to-end operation. Various tests and experiments related to each area is described and shown in this document.

9.2 Demonstrations Key Steps

The table below lists the AMI demonstrations and their key steps for completion. These eight (8) major activities were successfully undertaken as part of the AMI effort. The steps taken toward accomplishing every Demo/Use Case is listed in the "Key Steps" column.

SOPO	Demo/Use Case	Key Steps
• **AMI communications and Smart Meter deployment**	AMI-1 Install Head-End	o Procurement process were completed. Best vendor who meets more requirements at the most reasonable cost is selected as the 'AMI Vendor'. o The contract with AMI Vendor is signed o The Head-End system is installed in LADWP's production environment o The LADWP AMI Operators are trained and can maintain the Head-End System
	AMI-2 Design Communication Network & Select Site	o LADWP has provided the location and type of meters to the AMI Vendor. o The contract and Statement of Work with AMI Vendor are signed. o LADWP has provided the location and type of the meters (form factors so that the AMI vendor can propose a compatible AMI meter) to the AMI Vendor. o LADWP has provided the location and ID of permissible poles and substations where communication network devices can be installed to the AMI Vendor. o LADWP and the AMI Vendor agree on the location of the communication types and devices. o LADWP has calculated the cost estimates to install the communication devices.
	AMI-3 Design Back Haul Communication Network	o LADWP has provided the location and type of the meters to the AMI Vendor. o The contract and Statement of Work with AMI Vendor are signed. o LADWP has provided the location and type of the meters to the AMI Vendor. o LADWP and the AMI Vendor agree on the location of the communication types and devices. o LADWP has calculated the cost estimates to install the communication devices.

	AMI-4 Construction / Site Preparation for Communication Devices	o The AMI Vendor and LADWP have agreed on the type and location of the communication devices. o LADWP has obtained joint use agreements in areas of deployment if applicable. o LADWP (Standards Group) has approved the devices (repeaters, collectors, communication routers). o LADWP has installed and is maintaining the AMI vendor Head-End system. o LADWP has integrated the AMI vendor Head-End system with MV-90/MDM/CIS (as applicable). o LADWP can create and close work requests for telecom field work o The site is ready to accept a communication device installation. o The work request is closed.
	AMI-5 Install Communication Device	o The AMI Vendor and LADWP have agreed on the type and location of the communication devices. o LADWP has obtained joint use agreements in areas of deployment if applicable. o LADWP (Standards Group) has approved the devices (repeaters, collectors, communication routers). o LADWP has installed and is maintaining the AMI vendor Head-End system. o LADWP has integrated the AMI vendor Head-End system with MV-90/MDM/CIS (as applicable). o LADWP can create and close work requests for telecom field work. o The selected site has been prepared for the communication device installation. o A communication device has been installed. o The work request is closed.

	AMI-6 Install AMI Meter (Power/PQ Meter)	o The AMI Vendor and LADWP have agreed on the type and location of the AMI meters. o The contract and Statement of Work with AMI Vendor are signed. o LADWP has provided the location and type of the meters to the AMI Vendor. o LADWP (AMI Group) has approved the AMI meters. o LADWP has installed and is maintaining the AMI vendor Head-End system. o LADWP has integrated the AMI vendor Head-End system with MV-90/MDMS/CIS (as applicable). o The AMI meter is installed o The work request is closed.
	AMI-7 Perform Communication Network Tuning	o The installation of an AMI meter and/or a communication device has been completed. o AMI meters are installed. o Communication devices are installed. o The Head-End system is installed. o Meter communication is stable and has met the agreed upon threshold.
	AMI-8 Operate AMI System	o The Head-End system is in LADWP's production environment. o AMI Operators are trained and can maintain the Head-End System.

Table 59: AMI demonstrations' key steps

9.2.1 Metering System

This demonstration area was responsible for the step by step process of procuring Smart Meters and building configuration programs for various metering applications; the preparation, testing, and installation of residential AMI electric meters, AMI meters for demand applications, Time of Use meters, AMI meters monitoring Electric Vehicle chargers; performing "accuracy tests" (calibration tests) and acceptance tests on meters; developing and using an AMI Asset Management System to track inventory and installation of meters; and replacing and returning defective meters to the vendor. Deployment of the metering system covers the following use cases:

- Use Case 1 – Install Head – End
- Use Case 2 – Design Communication Network & Select Site
- Use Case 3 – Design Back Haul Communication Network

- Use Case 6 – Install Various AMI Meters
- Use Case 8 – Operate AMI System

Itron's water meter technology was not ready; therefore, the water meter was not deployed.

Methodology

To demonstrate and meet the success criteria for this demonstration area, the AMI Project team procured meters that met the requirements for this project. After procurement, LADWP tested a sample of the meters in-house before installation. Next, the AMI team mapped out location for the meters and worked with LADWP Meter Services division to install all of the meters.

AMI meters provided insight into the grid's edge by returning in-depth, timestamped information about occurrences at the customer premise. This data was integrated into utility back office systems, such as an Outage Management System (OMS) and a Grid Analytics Platform, allowing System Operators in the Smart Grid Operations Center (SGOC) to analyze historical power outages and react, in real-time, to new power outages. This was achieved by integrating the AMI data with OMS and an Analytics Platform, called K-Grid.

The OMS was integrated with the AMI data to automatically group outages with known jobs and create individual customer outage tickets for ungrouped outages. Based on the test results, LADWP found that, in many cases, power outages were received by OMS within seconds of occurrence. In the interim business process, LADWP representatives were contacting customers to confirm the AMI power outage and dispatching crews accordingly.

In the SGOC, System Operators tested, monitored, and analyzed power outages using the monitoring system (K-Grid application), which provided real-time updates on power outages and restorations. As part of the Smart Grid Regional Demonstration Project (SGRDP), System Operators power cycled a test meter in the Operations Center to determine the accuracy of the data received and to test for potential meter issues in outage scenarios. In addition, System Operators analyzed large power outages and compared the AMI data to electric trouble reports.

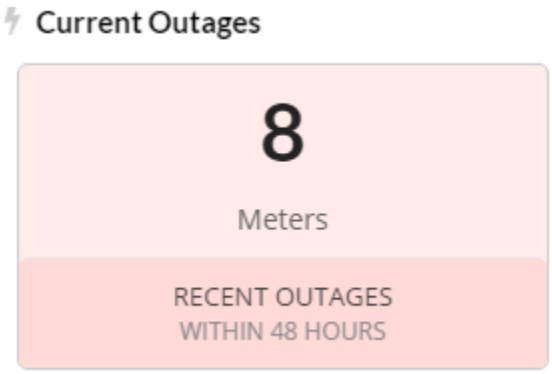


Figure 83: Current Outages

Figure 84 represents all the PON and PRN meter events that have been received by the system within a set period of time. These events are used to investigate power outages, potential issues at the customer premise, reliability issues, and metrics calculations.

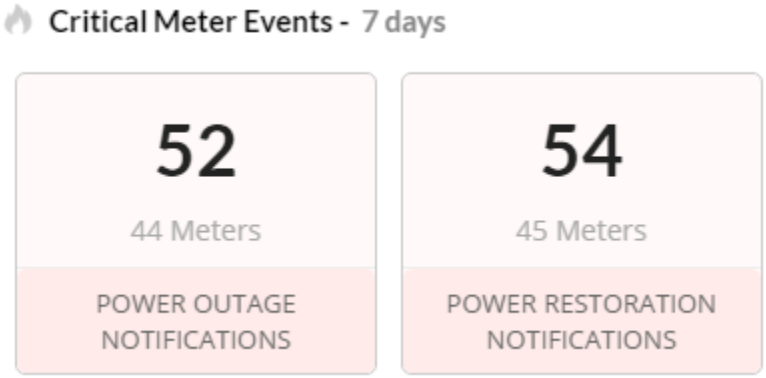


Figure 84: Power Outage and Restoration Meter Events

Figure 85 is a map of the power outages to allow System Operators to quickly identify if an outage is localized to a specific geographic area.

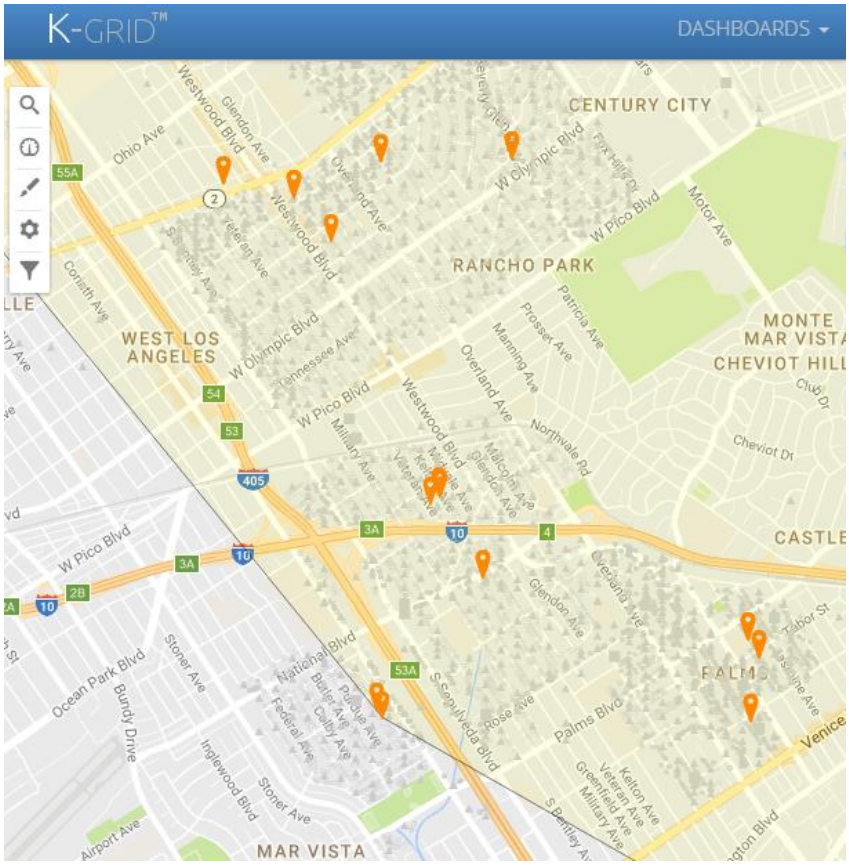


Figure 85: Meter Outage Map

In the following example, meter 1387032 experienced three power outages within a period of four minutes on 8/8/16. Figure 86 is a sample of PONs that was received from the AMI meters. Figure 87 represents a sample of PRNs from the AMI meters.

#	Meter	Received When	Timestamp	Event Type
1	1387032	2016-08-08 13:32:54	2016-08-08 13:32:27	Primary Power Down
2	1387032	2016-08-08 13:30:35	2016-08-08 13:30:11	Primary Power Down
3	1387032	2016-08-08 13:28:49	2016-08-08 13:28:29	Primary Power Down
4	1421071	2016-08-08 13:22:13	2016-08-08 13:21:53	Primary Power Down
5	1495932	2016-08-08 13:02:03	2016-08-08 13:01:39	Primary Power Down
6	1426735	2016-08-08 12:54:12	2016-08-08 12:53:53	Primary Power Down
7	1424727	2016-08-08 12:40:23	2016-08-08 12:40:01	Primary Power Down
8	1429360	2016-08-08 12:35:55	2016-08-08 12:35:26	Primary Power Down
9	1457480	2016-08-08 12:31:53	2016-08-08 12:31:29	Primary Power Down
10	1458343	2016-08-08 12:07:15	2016-08-08 12:06:45	Primary Power Down
11	1424229	2016-08-08 11:59:07	2016-08-08 11:58:50	Primary Power Down
12	1440859	2016-08-08 11:58:13	2016-08-08 11:57:53	Primary Power Down
13	1388466	2016-08-08 11:16:57	2016-08-08 11:16:41	Primary Power Down
14	1427688	2016-08-08 11:07:05	2016-08-08 11:06:47	Primary Power Down
15	1428887	2016-08-08 11:05:00	2016-08-08 11:05:03	Primary Power Down
16	1455735	2016-08-08 11:01:51	2016-08-08 11:01:19	Primary Power Down
17	1445067	2016-08-08 10:46:06	2016-08-08 10:45:13	Primary Power Down
18	1385385	2016-08-08 10:26:52	2016-08-08 10:26:31	Primary Power Down
19	1495722	2016-08-08 10:02:03	2016-08-08 10:01:40	Primary Power Down
20	1438579	2016-08-08 09:44:44	2016-08-08 09:44:31	Primary Power Down

Figure 86: Power Outages Notifications

#	Meter	Received When	Timestamp	Event Type
1	1387032	2016-08-08 13:35:33	2016-08-08 13:33:01	Primary Power Up
2	1387032	2016-08-08 13:31:36	2016-08-08 13:30:27	Primary Power Up
3	1387032	2016-08-08 13:29:34	2016-08-08 13:28:59	Primary Power Up
4	1495932	2016-08-08 13:02:52	2016-08-08 13:02:12	Primary Power Up
5	1426735	2016-08-08 12:56:01	2016-08-08 12:55:25	Primary Power Up
6	1426735	2016-08-08 12:55:03	2016-08-08 12:54:08	Primary Power Up
7	1424727	2016-08-08 12:40:59	2016-08-08 12:40:04	Primary Power Up
8	1429360	2016-08-08 12:38:03	2016-08-08 12:37:12	Primary Power Up
9	1429360	2016-08-08 12:38:03	2016-08-08 12:37:12	Primary Power Up
10	1429360	2016-08-08 12:38:03	2016-08-08 12:35:55	Primary Power Up
11	1458343	2016-08-08 12:08:33	2016-08-08 12:07:50	Primary Power Up
12	1424229	2016-08-08 11:59:39	2016-08-08 11:58:55	Primary Power Up
13	1388466	2016-08-08 11:18:46	2016-08-08 11:18:24	Primary Power Up
14	1427688	2016-08-08 11:09:21	2016-08-08 11:08:58	Primary Power Up
15	1428887	2016-08-08 11:06:15	2016-08-08 11:05:46	Primary Power Up
16	1428887	2016-08-08 11:06:15	2016-08-08 11:05:52	Primary Power Up
17	1422459	2016-08-08 10:57:06	2016-08-08 10:22:17	Primary Power Up
18	1455879	2016-08-08 10:10:14	2016-08-08 10:07:28	Primary Power Up
19	1455879	2016-08-08 10:10:14	2016-08-08 10:07:19	Primary Power Up

Figure 87: Power Restorations Notifications

SGOC System Operators worked with OMS and other teams to analyze real-time outages, research historical outages, investigate issues at the customer premise, calculate outage metrics, and identify potential reliability issues.

In Figure 88, the "Possible Transformer Outages" module is depicted. AMI data, along with transformer asset information is used to group outages by transformer. This module can be used by System Operators to react to potential device outage situations.



Figure 88: Possible Transformer Outages

Historically, utilities dispatch crews, generated outage tickets, and calculated outage metrics based on customer calls. With the introduction of AMI data, utilities were able to investigate system disturbances and dispatch crews without the need for a customer phone call. This led to heightened situational awareness and increased reliability and customer satisfaction.

Various Types of Meters	Qty Installed
7FM9 Meters: Demand application for C&I and large residential	895
Electric Vehicle (EV) Meters: Public Locations **7FED9, 7AED9, 73FED9, 73AED9, 73AEYPD109**	167
Electric Vehicle (EV) Meters: Rebate Locations **7AED9, 73AED9**	305
7FY9 Meters: residential with neutral wire	1942
7A9 Meters: regular residential with cellular communication	1953
7F9 Meters: regular residential with RF mesh communication	45917
Solar Meters: Pilot installation at FiT, SiP Unit, and SIP Net locations, per ECC's request, in cooperation with Solar team	12
Total	**51191**

Table 60: Quantity of Installed Smart Meters

Description of deployed meters:

7FM9 Meters: These smart meters cover the 'demand' application which means providing of Maximum KW Demand by the meter, besides the KWH usage. These meters are equipped with a 'demand switch' on the front-face of the meter to make 'demand reset' possible for the meter reader.

Rebate Electric Vehicle (EV) Charger Meters: These meters are installed at the electric vehicle chargers at customers' locations who have leveraged the 'rebate' program that LADWP offered to customers who install EV charger at their house.

Public Electric Vehicle (EV) Charger Meters: These meters are installed at the electric vehicle chargers at public locations, such as LADWP's parking garage or City Hall.

7FY9 Meters: Residential meters with a neutral from WYE-connection of the service. This type of meters is also known as Form Factor 12S.

7A9 Meters: Residential Form 2S meter, with cellular communication module. For this project, Verizon Wireless is the carrier of choice to communicate with cellular meters. Itron Cellular Solution service is also known as ICS.

7F9 Meters: The majority of installed meter are this type. Form 2S residential meters with RF module that can communicate with FCS handheld up to the point that it communicates with Cisco data collector, aka, Collected Grid Router (CGR).

Solar Meters: Smart grid team worked with the Energy Control Center (ECC) and the LADWP's Solar team to implement a pilot implementation of smart meters at various cases of solar scenarios. Implementation of photovoltaic panels in LADWP follows one of the following two scenarios: Feed-in-Tariff (FiT), and Solar Incentive Program (SIP). Smart meters were installed at both instances.

Success Criteria

The success criteria for Metering System included the delivery and installation of all meters, the successful transmittal of data, and a fully functional Asset Management System along with documentation. Additionally, reports on all tests performed on the meters were also generated as a part of the success criteria for the demonstration area. These criteria were met. The above meters were implemented and two-way communication was successfully stablished with them.

In this project, "OpenWay Centron" meters made by Itron were deployed. Photo of a typical meter follows:



Figure 89: OpenWay Centron meter

9.2.2 Communication Network

This demonstration was for designing the communication network and the back haul communication network, installation of the Cisco Connected Grid Routers and RF Range Extenders, performing communication network "tuning", installation of the Network Management System (NMS), monitoring communications between the meters and CGRs through the NMS, demonstrating the effect of the RF Range Extender to improve communication with meters, and creating sample maps of all RF meters for the LADWP AMI system.

Deployment of the Communication Network covered the following use cases:

- Use Case 4 – Construction / Site Preparation for Communication Devices
- Use Case 5 – Install Communication Device
- Use Case 7 – Perform Communication Network Tuning

The following diagrams indicate the communication networks and its relation to the meters and the OpenWay solution as a whole:

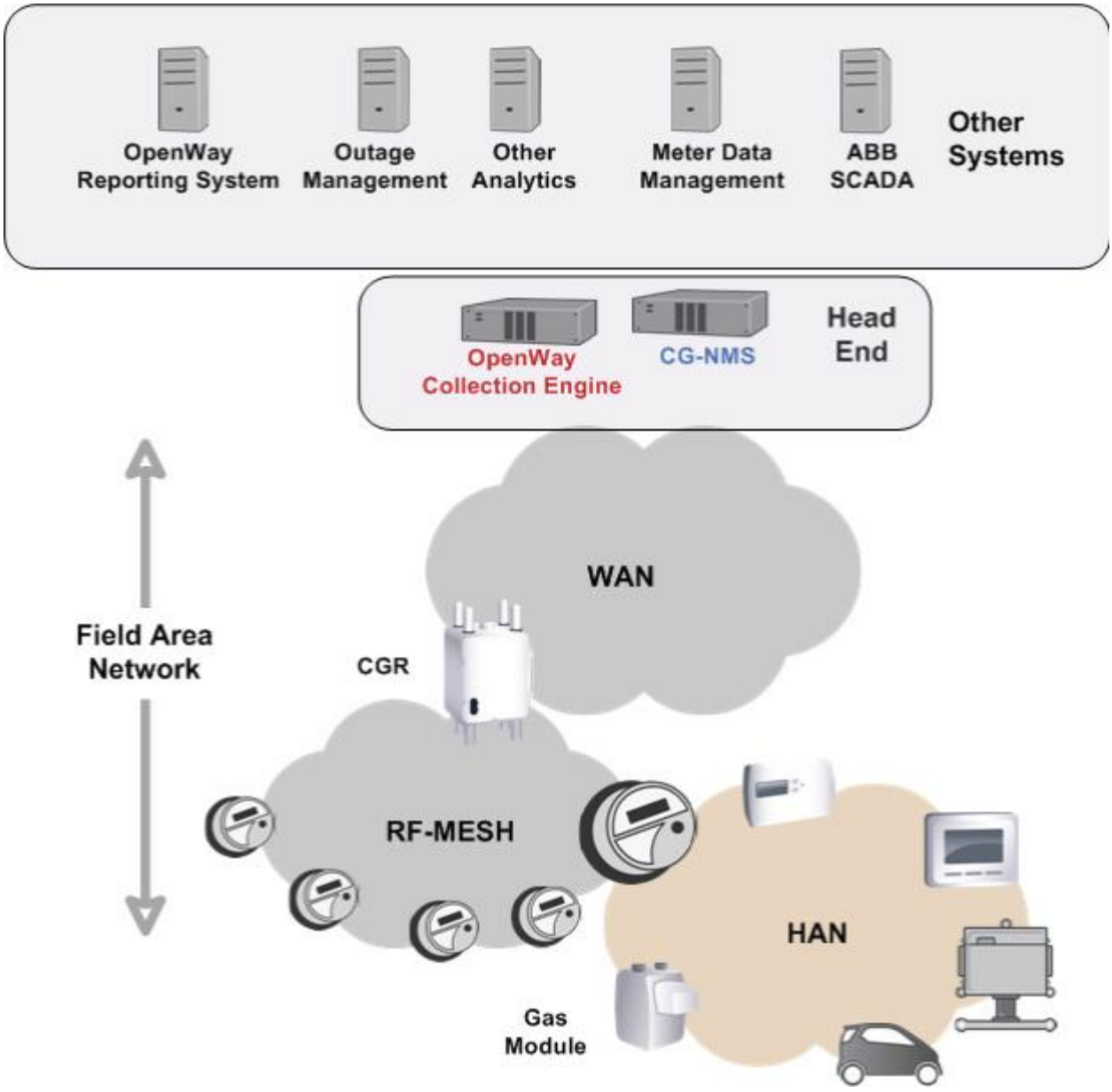


Figure 90: Solution Architecture Diagram

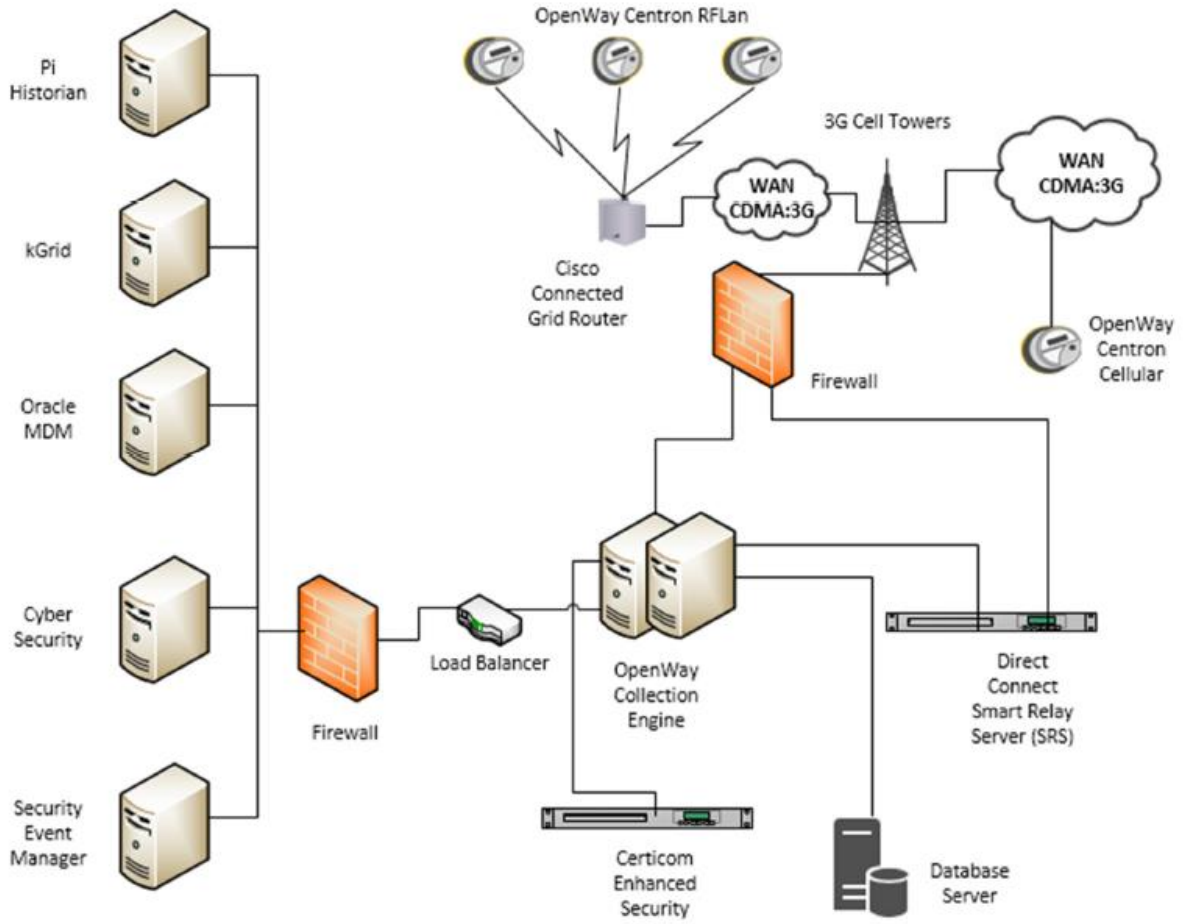


Figure 91: Network Architecture Diagram

Methodology

To demonstrate the use cases and meet the success criteria for this demonstration area, the AMI Project team implemented two different communication networks: cellular and RF. Following procurement of devices, the team worked with LADWP Construction crews to install Cisco Connected Grid Routers (CGR) and RF Range Extenders (RRE). This system established a two-way connection between all meters and the data collection engine. The Cisco Network Management System (NMS) is also deployed to monitor communications between the meters and Grid Routers.

Technologies Deployed

Connected Grid Router (CGR):

This device is also known as 'data collector'. It communicates with electric meters from one side, via 900 MHz RF mesh network, and with the back office system on the other end, via Verizon wireless network or Ethernet. In this project, five (5) CGR devices backhauled the data via Ethernet (four were installed at

Department's substations, and one was installed at Department's headquarters' parking lot), and the remaining were installed on top of poles, backhauling data through cellular network. A photo of a CGR device is provided below:



Figure 92: CGR

Every CGR can collect data from up to 4,000 electric meters. However, the manufacturer does not recommend loading a CGR more than about 50% of this capacity for a long time.

RFLAN Range Extender (RRE):

This device is also known as 'data repeater'. Every Centron OpenWay meter can also function as repeater. In areas where the deployment does not create a dense RF mesh, RREs can help to saturate the RF mesh, so the signal propagation takes place, and data finds its 'path' to the CGRs, back to the utility. A photo of a RRE device is provided below:



Figure 93: RRE

The following table indicates a sample of data collection from a meter, installed at a solar customer:

Serial Number	66784		
Electronic Serial Number	2.16.840.1.114416.1.24 .66784		
Interactive Read Time	3/1/2016 8:23		
Time Zone	(UTC-08:00) Pacific Time (US & Canada); Tijuana		
Requested Time Span	2/29/2016 12:00:00 AM - 3/1/2016 12:00:00 AM		
Job Status	Successful		
Job Duration	0:01:34		
Register Data			
Register Name	Value	Time of Occurrence	Source
ccum W d	729.45	3/1/2016 8:24	Current
ccum W d Rate A	729.45	3/1/2016 8:24	Current
ccum W d Rate B	646.7	3/1/2016 8:24	Current
ccum W d Rate C	722.025	3/1/2016 8:24	Current
cum W d	0	3/1/2016 8:24	Current
cum W d Rate A	0	3/1/2016 8:24	Current
cum W d Rate B	0	3/1/2016 8:24	Current
cum W d Rate C	0	3/1/2016 8:24	Current
ins V(a)	281.525	3/1/2016 8:24	Present
Instantaneous Watts Delivered Aggregate	155.5669	3/1/2016 8:24	Present

Instantaneous Watts Delivered Phase A	56.8379	3/1/2016 8:24	Present
Instantaneous Watts Delivered Phase B	49.2706	3/1/2016 8:24	Present
Instantaneous Watts Delivered Phase C	49.4584	3/1/2016 8:24	Present
Instantaneous Watts Received Aggregate	0	3/1/2016 8:24	Present
Instantaneous Watts Received Phase A	0	3/1/2016 8:24	Present
Instantaneous Watts Received Phase B	0	3/1/2016 8:24	Present
Instantaneous Watts Received Phase C	0	3/1/2016 8:24	Present
max W d	729.45	5/1/2015 13:15	Current
max W d Rate A	729.45	5/1/2015 13:15	Current
max W d Rate B	646.7	6/11/2015 13:00	Current
max W d Rate C	722.025	5/16/2015 11:15	Current
Number of Demand Resets	0	3/1/2016 8:24	Present
Number of Inversion Tampers	0	3/1/2016 8:24	Present
Number of minutes on battery carryover	168567	3/1/2016 8:24	Present
Number of Power Outages	4	3/1/2016 8:24	Present
Number of Removal Tampers	1	3/1/2016 8:24	Present
Number of times programmed	3	3/1/2016	Present

		8:24	
Wh d	675083.625	3/1/2016 8:24	Current
Wh d Rate A	185810.65	3/1/2016 8:24	Current
Wh d Rate B	205292.8375	3/1/2016 8:24	Current
Wh d Rate C	283980.1375	3/1/2016 8:24	Current

Table 61: Sample of data collection from a meter - Solar customer

The following table indicates a sample of load-profile data collection from a meter, installed at the Project's Garage of the Future (GOF):

Interval End Date/Time	Wh d	Wh r	Wh net	VAh d
2/1/2016 12:15:00 AM	1212	0	1212	1247
2/1/2016 12:30:00 AM	1230	0	1230	1266
2/1/2016 12:45:00 AM	1243	0	1243	1277
2/1/2016 1:00:00 AM	1258	0	1258	1294
2/1/2016 1:15:00 AM	1376	0	1376	1410
2/1/2016 1:30:00 AM	1380	0	1380	1413
2/1/2016 1:45:00 AM	1380	0	1380	1412
2/1/2016 2:00:00 AM	1149	0	1149	1184
2/1/2016 2:15:00 AM	66	0	66	141
2/1/2016 2:30:00 AM	99	0	99	160
2/1/2016 2:45:00 AM	139	0	139	183
2/1/2016 3:00:00 AM	139	0	139	182
2/1/2016 3:15:00 AM	134	0	134	180
2/1/2016 3:30:00 AM	22	0	22	114
2/1/2016 3:45:00 AM	22	0	22	114
2/1/2016 4:00:00 AM	22	0	22	115
2/1/2016 4:15:00 AM	22	0	22	115
2/1/2016 4:30:00 AM	22	0	22	114
2/1/2016 4:45:00 AM	22	0	22	114
2/1/2016 5:00:00 AM	21	0	21	115
2/1/2016 5:15:00 AM	22	0	22	114
2/1/2016 5:30:00 AM	22	0	22	115
2/1/2016 5:45:00 AM	22	0	22	114
2/1/2016 6:00:00 AM	21	19	2	113
2/1/2016 6:15:00 AM	0	1110	-1110	0
2/1/2016 6:30:00 AM	0	1112	-1112	0
2/1/2016 6:45:00 AM	0	1111	-1111	0
2/1/2016 7:00:00 AM	0	1099	-1099	0
2/1/2016 7:15:00 AM	0	1100	-1100	0
2/1/2016 7:30:00 AM	13	641	-628	16
2/1/2016 7:45:00 AM	35	0	35	44
2/1/2016 8:00:00 AM	36	0	36	44
2/1/2016 8:15:00 AM	35	0	35	43
2/1/2016 8:30:00 AM	35	0	35	44

Figure 94: sample of load-profile data collection from a meter - GOF

The following screenshot indicates a sample of reporting Power Outage Notification (PON) from meters:

Meter	Received When	Timestamp	Event Type	ESN
1499471	3/24/2016 7:41		Primary Power Down	2.16.840.1.114416.1.24.1499471
1391607	3/24/2016 8:12	3/24/2016 8:11	Primary Power Down	2.16.840.1.114416.1.24.1391607
1404917	3/24/2016 8:12		Primary Power Down	2.16.840.1.114416.1.24.1404917
1391607	3/24/2016 8:14	3/24/2016 8:13	Primary Power Up	2.16.840.1.114416.1.24.1391607
1404917	3/24/2016 8:16	3/24/2016 8:14	Primary Power Up	2.16.840.1.114416.1.24.1404917
1494342	3/24/2016 8:17	3/24/2016 8:13	Primary Power Up	2.16.840.1.114416.1.24.1494342
1494342	3/24/2016 8:27	3/24/2016 8:26	Primary Power Down	2.16.840.1.114416.1.24.1494342
1494342	3/24/2016 8:28	3/24/2016 8:27	Primary Power Up	2.16.840.1.114416.1.24.1494342
1428556	3/24/2016 10:51	3/24/2016 10:50	Primary Power Down	2.16.840.1.114416.1.24.1428556
1428556	3/24/2016 10:52	3/24/2016 10:51	Primary Power Up	2.16.840.1.114416.1.24.1428556
1383742	3/24/2016 11:27	3/24/2016 11:27	Primary Power Down	2.16.840.1.114416.1.24.1383742
1383742	3/24/2016 11:28	3/24/2016 11:27	Primary Power Up	2.16.840.1.114416.1.24.1383742
1439760	3/24/2016 11:28	3/24/2016 11:27	Primary Power Down	2.16.840.1.114416.1.24.1439760
1465743	3/24/2016 11:41	3/24/2016 11:40	Primary Power Down	2.16.840.1.114416.1.24.1465743
1504213	3/24/2016 13:16	3/24/2016 13:15	Primary Power Down	2.16.840.1.114416.1.24.1504213
1455897	3/24/2016 13:21	3/24/2016 13:20	Primary Power Down	2.16.840.1.114416.1.24.1455897
1465268	3/24/2016 13:31	3/24/2016 13:31	Primary Power Down	2.16.840.1.114416.1.24.1465268
1455897	3/24/2016 14:01	3/24/2016 14:00	Primary Power Up	2.16.840.1.114416.1.24.1455897
1504213	3/24/2016 14:38	3/24/2016 14:38	Primary Power Down	2.16.840.1.114416.1.24.1504213
1465262	3/24/2016 14:40	3/24/2016 14:40	Primary Power Down	2.16.840.1.114416.1.24.1465262
1464232	3/24/2016 14:48	3/24/2016 14:47	Primary Power Down	2.16.840.1.114416.1.24.1464232
1464232	3/24/2016 14:48	3/24/2016 14:48	Primary Power Up	2.16.840.1.114416.1.24.1464232
1451061	3/24/2016 16:12	3/24/2016 16:11	Primary Power Up	2.16.840.1.114416.1.24.1451061
1450359	3/24/2016 16:57	3/24/2016 16:57	Primary Power Down	2.16.840.1.114416.1.24.1450359
1450359	3/24/2016 17:00	3/24/2016 16:57	Primary Power Up	2.16.840.1.114416.1.24.1450359
1439760	3/24/2016 18:44	3/24/2016 18:41	Primary Power Up	2.16.840.1.114416.1.24.1439760
1439760	3/24/2016 18:44	3/24/2016 18:43	Primary Power Up	2.16.840.1.114416.1.24.1439760
1504940	3/25/2016 3:09		Primary Power Down	2.16.840.1.114416.1.24.1504940
1504940	3/25/2016 4:19	3/25/2016 4:16	Primary Power Up	2.16.840.1.114416.1.24.1504940
1499463	3/25/2016 7:41		Primary Power Down	2.16.840.1.114416.1.24.1499463
1495903	3/25/2016 8:23	3/25/2016 8:21	Primary Power Down	2.16.840.1.114416.1.24.1495903
1390875	3/25/2016 8:43	3/25/2016 8:43	Primary Power Down	2.16.840.1.114416.1.24.1390875
1499105	3/25/2016 8:43		Primary Power Down	2.16.840.1.114416.1.24.1499105
1495903	3/25/2016 8:50	3/25/2016 8:42	Primary Power Up	2.16.840.1.114416.1.24.1495903
1390875	3/25/2016 8:53	3/25/2016 8:52	Primary Power Up	2.16.840.1.114416.1.24.1390875
1495219	3/25/2016 8:57	3/25/2016 8:57	Primary Power Down	2.16.840.1.114416.1.24.1495219

Figure 95: Sample of reporting Power Outage Notification (PON) from meters

Technologies Deployed

Equipment Overview	Total Planned	Installed
CGRs – Cisco Connected Grid Routers	59	59
RFLAN Range Extender	27	27

Table 62: Communication Network Equipment List

Success Criteria

The success criteria for the Communication Network would be a network to be able to reach out to meters for two-way communication, and read at least 90% of the installed meters. Additionally, the complete installation of all CGRs and RREs in addition to installation and procedural documentation, the installation of the Network Management System, and the completion of all required testing on all equipment were required as a part of the success criteria. These criteria were met.

The following screenshot indicates the general idea behind the Network Management System (NMS), providing the status of 'up' and 'down' CGR units at any given time, as well as the time and information associated with various events:

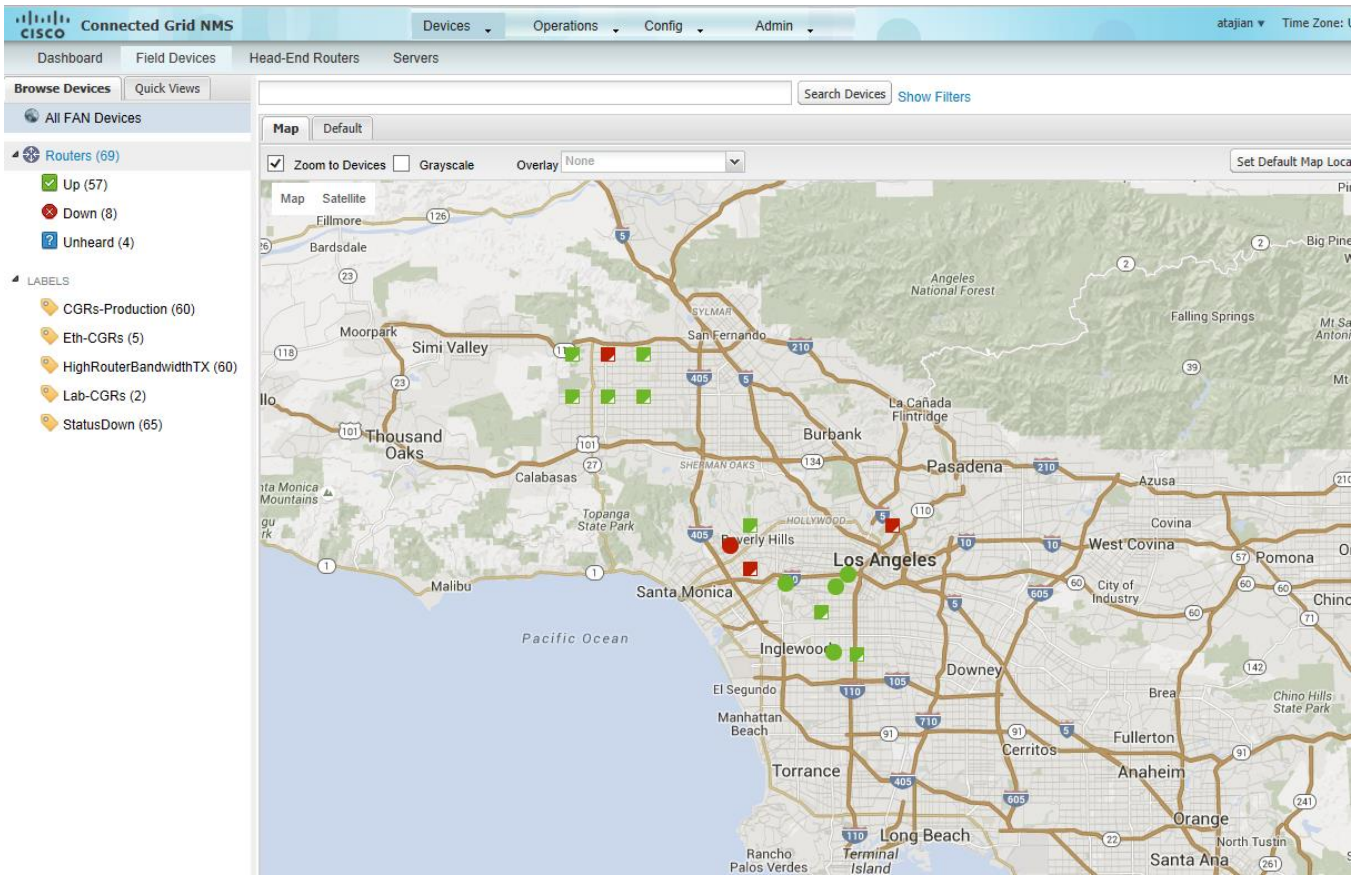


Figure 96: Network Management System (NMS) Concept

9.2.3 Back Office and Data Collection

This demonstration area was the step by step process to install the head-end system, prepare at least one form of reporting system, utilize remote two-way communication using the head-end system, read events

and exceptions from a meter through the head-end system, and take action based on a received event or exception to correct an issue in the AMI system.

Methodology

To demonstrate the use cases and meet the success criteria for this demonstration area, the AMI Project team installed, configured, tested, and integrated the Itron Collection Engine (CE) head-end.

The following screenshot indicates the Collection Engine user interface:



Figure 97: CE Interface

The LADWP ITS organization led the effort to install and implement a Meter Data Management (MDM) system, and a Customer Information System (CIS). The implemented MDM system is known as 'Oracle Utilities' and the implemented CIS system is named Customer Care and Billing (CC&B).

An adapter was developed to integrate this MDM with the Collection Engine headend.

Technologies Deployed

Equipment Overview	Total Planned	Installed
Oracle Utilities Meter Data Management (MDM)	1	1
Customer Care and Billing (CC&B)	1	1
OpenWay Collection Engine	1	1

Table 63: Back Office and Data Collection Equipment List

Success Criteria

The success criteria for Back Office and Data Collection included the successful completion of all use cases. Additionally, the head-end system must be in the LADWP's production environment and LADWP AMI Operators must be trained to maintain the head-end system. These criteria have been met.

9.2.4 End-to-End Operation

As part of the end-to-end experiment, a set of meters were selected to include various types, models, and configuration programs. LADWP has selected to install the AMI meters in five concentrated areas in and around the USC campus; in and around the UCLA campus; and meters contained in a circuit around the existing EV demonstration site to support partnerships with USC and UCLA in the SGRDP. Data interrogations were sent to meters, and their responses were monitored. The end-to-end test was performed to ensure the system can successfully operate as a whole, from meter to the communication networks to data collection mechanism.

Please see Appendix D of this document for a description of end-to-end tests and their results.

9.3 Problems Encountered

Type	Risk Description	Likelihood of Occurrence	Cost Schedule Impact	Risk Consequence	Risk_Mitigation
Technical	Itron network design needs to be revisited, as "holes" are identified in the mesh	Medium	Medium	• Failure of the program to meet one or more key objectives. • Cost or schedule overruns	Worked with Itron on daily basis to resolve the issue. Itron engineers showed up onsite to resolve the issue. Installed more meters and CGR. The issue was successfully resolved.

Technical	Although the project schedule has been extended, further delays in Meter Data Management (MDM) go-live will impact Meter data storage as planned, data may not be distributed to the data subscribers, and neither commands nor web services can be initiated through the head end.	High	Med	• Failure of the program to meet one or more key objectives. • Substantial cost or schedule overruns	MDM was finally setup, with running and collecting data. Tests were also successfully performed for remote disconnect/reconnect.
Staffing	Test Plans and scripts not defined	Medium	Medium	• Failure of the program to meet one or more key objectives. • Substantial cost or schedule overruns	Project resources were tracked to complete the test scripts. AMI developed system acceptance test plan. The test plan was successfully followed and concluded.
Technical	Changes have been requested to be made to configuration of 7FM9 meters, now waiting on Itron to make those changes and deliver new 1st article for testing; May delay deployment of demand meters.	Low	Low	• Failure of the program to meet one or more key objectives. • Substantial cost or schedule overruns	Worked with vendor, successfully updated configuration program.
Staffing	Delay in installation of Data Power, impacts end to end integration. Data Power provides security rules between MDM and Head End.	Med	Med	• Substantial cost or schedule overruns	ITS worked on implementing Data Power application. Completed Integration between DR and Headend. Installed Data Power (for SGRDP to ensure 2 systems have a layer of protection). Data Power was removed since it didn't start working by the end of February 2016.

Technical	Centron OpenWay Direct Connect Meters have not been used before, potential glitches may occur as this is the first installation of this type. These meters have been ordered and are not yet received.	Low	Low	• Failure of a team to meet one or more team objectives, with no material trickle-up impact to the program • Minor schedule or cost overruns, with no material trickle-up impact to the program	AMI team worked with Itron to resolve the issue. Direct Connect meters were tested, configured, and successfully used in the project.
Technical	Integration of Oracle Adapter is not complete to establish communication between OpenWay Collection Engine and Oracle SGG/MDM. The Adapter is needed for the head-end to communicate with MDM. This is a new technology which has neither been tested or deployed in other utilities, as a result, potential glitches may occur as this is the first installation of this application.	Low	Low	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns	Oracle resources have been engaged with this implementation. Integration was completed.
Staffing	Resources are not designated for all required functions to operate, maintain, and troubleshoot the system. Resources will be needed to operate three major areas: Metering System, Communication Network, and Back Office System.	Low	Low	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns	Smart Grid Operation Center was created to mitigate this risk.

Security	Shipment of lock rings has not completely arrived, which poses as a security risk.	Low	Low	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Cost or schedule overruns	AMI met w/ Highfield and regular shipments were scheduled.
Technical	The newly implemented CC&B requires templates and configurations for every type and model of meters which the AMI project was not aware of before. The loading of AMI meters to inventory can be delayed due to building these new templates and configurations.	Medium	Low	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns	Meter Engineering identified and trained resources to create and test meter templates. Serial number field has been added to CC&B.
Technical	19 CGRs did not communicate during October 2013	High	High	Failure to resolve CGR issues may impact end-to-end meter communications and goals for the AMI project	Worked with Itron, Cisco, and Verizon to resolve the issue. The issue turned out to be a system communication outage caused by Verizon's regular system update
Schedule	Inventory of communication equipment and meters is moving from Van Nuys to where Artesian Street, Meter Engineering has not defined the timeline and responsibilities	Low	Low		Worked with Meter Engineering to communicate with involved parties. Meters have been successfully transferred

Staffing	Meters may not all be installed by scheduled dates	Med	Med	Delay project schedule	AMI team had negotiations with management. Installations got back on schedule.
Schedule	DS-41 group is not allowing installation of CGR due to security purposes	High	Low	Delays of CGR Installation	Itron surveying surrounding area to identify potential pole installation locations. CGR was finally installed in the surrounding areas. Communication with meters is successful.
Technical	Smart Meters for EV chargers at city hall are unable to communicate due to insufficient cellular communication network.	High	Low	Inability to collect consumption data from EV Chargers installed in and around City Hall.	AMI team installed cellular meters at city hall, 4 will not communicated, 5 will communicate. The ones that communicate provide sufficient data for the purpose of SGRDP.
Stakeholder / Staffing	LADWP Smart Meters have generated an error message and need replacement / fixing.	High	Low	Customer dissatisfaction may lead to negative Smart Grid publicity, financial claims, and legal issues.	Business Process has been established to deal with future error messages. AMI team has a channel through Meter Engineering to report defective meters to the field personnel to replace.
Technical	GOF metering requirements have not been clearly defined.	Med	Med	Delay in data collection at GOF.	AMI and EV teams collaborated and finalized requirements. Meters successfully installed as planned.

Technical	MDM data collection has been delayed due to issues with data collection and Data Repository.	High	High	Web Portal delays may impact customer sign-up and participation for both CB and DR studies. Further delay will impact data collection period and quality of demonstrations.	Defects in the MDM were documented in the Rational System and followed up one by one in the order of priority. MDM finally became functional. Meter data interrogation is being performed 3 times per day.
Technical	Decisions need to be made about end-to-end implementation of the following issues: -Adding new unit-of-measures (KVARh, kVAh, PF) -Modifying significant figures for metering data	High	Med	Failure to come to a decision will result in delays in completion of installation of EV, PQ, and Solar meters	AMI team worked with MDM team and Oracle to resolve issues. Decision was made to add new registers at the MDM level. The functional design was prepared by Oracle to create an algorithm for this purpose. The algorithm was created and applied successfully.
Technical	No Direct Connect meters can be ordered at this time until collection engine gets updated to 6.1. Based on defects being noticed in v6.1, will wait for Oracle to certify v6.6 of Itron Collection Engine.	High	Low	Delay installation EV meters for level 3 charger. 5/21/15 New version of CE v6.1 has a few defects, such as new tags for some of the registers and "unknown" tags for some others. It also reports additional events.	CE was successfully upgraded to v6.1, and more Direct Connect meters were ordered as needed.
Technical	Smart Grid team communicated the list of potential defected meters with Field Meter and Test. To be visited and possibly replace. Field Meter and Test has not performed any work in that regard.	High	Med	There are more than 50 potential defected smart grid meters in the field at this time that can affect communication, as well as billing.	AMI team worked with 'Field Meter Test' and 'Account Services Unit' groups. Weekly meetings were held between AMI team and the groups mentioned above. The defects and incorrect information were evaluated and corrected in cases by

					case basis.
Schedule	Smart Grid team has requested Meter Lab to add letter "U" to the prefix of 144 EV meters to be used for installation at public EV chargers. Meter Lab has not done any work in that regard.	High	Med	Delay in installation of meters for public EV chargers	Meter lab added letter "U" to the prefix of badges for 144 meters as requested.
Technical	No specific standard procedure how to test a new type of meter. Every stakeholder suggests some requirements.	High	High	New requirements may impact schedule / cost impacting demonstration schedule and data collection	AMI team reached to an agreement with stakeholders above the testing of new type of meters for this project.
Technical	CGR NOS files not being encrypted using the right certificate.	High	High	12 CGRs went down as the result	AMI team worked with Itron and Cisco to obtain the right NOS files from the CGRs. The units that had stopped communication resumed communication.
Schedule	Non-communicative CGRs: Sixteen (16) CGRs are not communicating at this time, which has cause about 6,000 meters to became unreachable for interrogation	High	High	Would cause a schedule delay	Mitigated by resolving the expired certification issue with CISCO, Itron, and network engineers.
Schedule	CICT has delayed creation non-billing SP type. Installation of meters at public EV is dependent on this task	High	High	Would cause a schedule delay	Worked with stakeholders to install these meters similar to unit meters so they're not dependent on such SP type. Meters were installed at JFB parking

					lot as planned.
Technical	Contractor is not responsive to the issues regarding communication between CE and OMS.	Med	Med	Potential challenges in communication b/t Collection Engine PD environment and OMS	Escalate to CGI leadership. Replaced resource, and issues were resolved.
Technical	Type of sockets that have been installed for level 3 chargers seems to be incorrect.	High	Low	Not able to installed currently purchased meters on Level 3 chargers, only 16 chargers affected	Issue was reported to the group that had installed the sockets, which is still being followed up.
Technical	AMI Unable to read installed meters EV rebate meters that were sitting in inventory due to Time Adjustment issue	High	Med	Not able to communicate with meter	The 'time' was adjusted on the meters that had experienced time-drift. Data was successfully collected from corrected meters.
Technical	AMI Intermittent CGR issues cause poor MDM reads	Med	Med	Negatively impacting read rates.	Worked with Ops Center and MDM team to plan re-interrogation of data when the reading rate is below 90%. The plan successfully worked for the purpose of SGRDP project. Additional CGRs planned to purchase as spare.

Table 64: Problems Encountered in AMI demonstrations

9.4 Lessons Learned

The major lessons learned from AMI Project:

- Many various organizations within a utility are involved with the successful implementation of an Advanced Metering Infrastructure. All organizations involved with metering, communication, and data collection need to get onboard early in the project and remain highly synched and collaborative throughout the project. In LADWP, some of the main organizations are listed below:
    - Metering:

        - Meter Engineering
        - Meter Test Lab
        - Meter Warehouse
        - Meter Setters
        - Field Meter & Test
        - Field Investigation
        - Work Management Information (WMIS)
        - Meter Readers
    - Communications:
        - ITS Network Security
        - ITS Databases
        - ITS SOA
        - Substations
        - DC&M
    - Data Collection:
        - CC&B / CIS
        - Meter Dara Management
        - ITS Network Security
        - ITS Databases
        - Meter Readers
- A 'cultural shift' is needed for a utility to adapt to an AMI system. Most utilities still only expect 'billing data' from their meters, but an AMI system looks beyond billing, the data can be used in various smart grid applications such as demand response, outage management, cyber security, etc.
- Training is crucial for the workforce of a utility to become familiar with new technologies associated with an AMI system.
- For AMI system to be successful, clear processes and procedures should be developed so the data is utilized in the most effective way.
- The current meter naming convention at LADWP requires time-consuming maintenance. The system of prefix, size, and nameplate color may not be needed for the future metering system. This needs to be evaluated and standardized. Considering that data from smart meters can be collected remotely, and disconnect/reconnect process can also be remotely managed, there will not be as many field personnel working with meters at site, therefore, there will be no reason to keep all the meter naming conventions the way it was designed years ago.
- There are many different configuration programs in LADWP metering management to configure digital meters (e.g., Config 60 for residential cases, Config 50 for demand meters, etc.), because various data needs to get collected from various type of customers. In future, with a full deployment of smart meters, this could become standardized and simplified, because the Meter Data Management – which will be the data repository of an inclusive AMI system, can collect time-stamped load profile of basic data, such as KWH-d, KWH-r, KVARH-d, and KVARH-r, and calculate the more complicated registers from it. This way, there would be no need for so many various configuration programs.

- There are currently a large number of configuration programs used at LADWP to configure meters. Tracking and maintenance of the convention requires excess time and resources. The number of configuration programs can be reduced, if load profile information of basic registers get collected from meters in the future and other registers get calculated from them in the back-office.
- Smooth transition between various stages of the project is critical for a large-deployment of AMI project. The project, usually tracks through the following stages:
    - Design
    - Planning
    - Implementation
    - Operation and Maintenance
- Like any other large-scale project, one Project Manager needs to monitor the following concepts closely and provide frequent reporting to the leadership:
    - Project Scope: the scope and objectives of the project needs to be clear. It is likely that when other organizations within the utility (e.g., PQ organization, Solar organization, etc.) are notified of the implementation of an AMI system will show interest in installation of smart meters in their domain and/or use the collected data for their own research and objectives. This would add burden to the original AMI project, and could potentially affect the cost, plan, and schedule. The leadership must not lose track of the main vision and goals of the project.
    - Project Budget: the project management needs to monitor the project costs closely and adjust the budget accordingly. Any change needs to be carefully examined prior to authorization. The overtime labor for example, can potentially have a significant effect on the total cost.
    - Project Schedule: the project schedule needs to consider various stakeholders and the 'domino effect' of one delay across the entire project. Adjustments need be solicited from stakeholders and get applied to the overall project schedule. It is imperative to keep a realistic timeline when preparing a project schedule for an AMI project, as delays are likely to happen at various stages of equipment delivery, installation, communication, mitigation and so on.
    - Project Resources: an AMI project would require resources at different areas of metering, communications, and data management. Meter deployment in the past mainly required resources familiar with the concept of electric power and metering, but 'smart metering' is more of an IT project than electric power project. The resources, therefore, need to be carefully selected to create a team of individuals with the variety of backgrounds and talents to fulfill various aspects of the project.
- Steady communication between various stakeholders, such as ITS, meter installers, CIS/MDM teams, communication group, etc. in form of weekly meetings and conference calls. Daily conference calls with the vendor at the beginning phase of the project to monitor the status closely.

- To create shared-drive for stakeholder to upload the files, pictures, and updates as quickly as possible.
- To experiment with a variety of solutions (RF vs. cellular for meter communication; cellular vs. fiber optics for CGRs, etc.) to see which works best under various circumstances
- To establish an operation center for daily monitoring of the system and responding to failures and defects. The events and alarms generated by meters can be utilized by various systems such as Outage Management System, Meter Readers, and Field Investigation.
- Keeping consistent with existing LADWP configuration programs in terms of information displayed on meter displays to prevent confusion of meter readers. Other needed data from meters is collected remotely from meters.
- Utility needs to be clear about its expectations from an AMI system and define them in a realistic manner.
- A central 'metering authority' needs to be put in place for various organizations to effectively collaborate with each other to accomplish the mission of the AMI project.
- Various organizations within the company need to get involved early in the project. Key organizations to involve are: ITS, Meter Shop, Billing, Customer Service and Communications.
- There's need for a cultural shift within the company to consider the meter as the utility's representative at the customer's location versus a billing device. Meters should be considered as not only data collection, but also HAN gateways, and monitoring devices for service power quality.
- The utility needs to be careful not to custom design the new technologies such as meter data management and Customer Information System (CIS) around the old metering policies such as prefixes and numbering schemas. The old policies and processes need to be redefined so the utility can benefit from the new technologies as much as possible such as remote reconfiguring of meters for new rates and functions.
- Hands-on training and on-the-job trainings have a critical role for a utility moving to the new era of smart grids and integrated grid. Meter installers need to become clear about every definition, e.g. Meter Number, Serial Number, Badge Number, Consumption, Demand, Time of Use, etc.
- Use of an Asset Management System along with meter barcodes and photos of removed meters would be critical to minimize the human errors in recording of meter activities and billing of removed meters.
- For an Advanced Metering Infrastructure system to have its full benefits, the automation needs to be from end to end. This is known in the industry as 'meter to cash' process. Many of technical and societal benefits occur when the data is collected remotely, and disconnect and reconnect of customers also take place remotely. Automating process for the data transmittal to MDM, and transmittal of final bill determinants to the CIS systems also add to the benefits. In other words: the more of processes get automated, the more of benefits get experienced through time.

9.5 Conclusion

The AMI system successfully operates as intended. The following lists success criteria for AMI demonstrations that were met and objectives that were accomplished:

- Ensuring that the data structure for all installed meters complies with the ANSI C12.19 standard

- Ensuring that load profile data, at 15-minute interval, is stored at meters and gets communicated with the head-end
- Ensuring a network monitoring application can monitor the data collectors and provides report on communicating vs. non-communicating data collectors
- Ensuring the meters and applications are protected, and unauthorized individuals cannot access them
- Ensuring the meters and communication equipment can get installed using the utility's work management system
- Ensuring that all AMI digital data transmissions comply with the ANSI C12.22 standard;
- Ensuring that all installed AMI and telecommunications equipment can securely communicate, without data loss or corruption and without a significant increase in data transmission latency;
- Providing more than one communication path for each AMI device (i.e., redundancy);
- Providing sufficient AMI functionality to enable adaptation to technology changes without needing to physically replace AMI meters and other intelligent devices (i.e., optimizing/extending the useful working life of equipment);
- Creating AMI solutions that are tailored to meet the needs of specific customer segments, such as residential, commercial, Demand application, EV Charger application, and Solar application;
- Supporting a key renewable energy generation – such as solar - and EV Charger deployment initiatives;
- Supporting various utility functions such as the following:
    - Billing by providing data to the MDM
    - Outage management – by providing outage data to the OMS, which enables improved power outage detection and management
    - Demand Response
- Providing a mechanism and strategy to carry out DR actions as DR message may be broadcast through the AMI communications network whenever load reduction is deemed necessary
- Ensuring that alarms and alerts are generated by meters as intended
- Enabling the preparation of timelier billing of customers for power to encourage better energy management by installation of Time of Use (TOU) meters at EV chargers
- Enabling scheduled/remote service connection and disconnection capability to manage move-out, payment delinquencies, etc. via demonstrations performed at UCLA dorms
- Ensuring that the back-office is fully functional in its communication with meters and handling reports.
- Enabling the capability to provide timely feedback to customers related to their electricity through the web portal (to encourage reduced energy consumption)

Customer Behavior was unable to conduct survey experiments related to customer rates and pricing options. Significant scheduling changes during Operations phase and a change in resources resulted in severe time constraints for CB portal build/deployment. As a result, no experiments were conducted via the CB portal.

The rates of meter communication and data collection fluctuate through the time due to various factors; however, the issues can get mitigated to return the system to its expected state of operation. The AMI system is valuable for an electric utility, as it can not only provide the billing information, but also the data that can help utility monitor the quality of service it is providing to the customers.

Both methods of available AMI communication (RF mesh, Cellular) are needed for a large AMI deployment. Each method should have its own use cases.

- The utility has more control and oversight over the RF mesh, but the system needs to be monitored, safeguarded, and maintained by the Utility. The Cellular network gets monitored and maintained by the carrier, but would require monthly payments to the wireless carrier company. Prior to a full-deployment, careful cost-benefit analysis needs to be made, to consider these options.

- Generally speaking, for the areas which houses are near each other and a 'dense' mesh can be formed, RF mesh technology is recommended; for areas that are disperse, cellular technology would be the solution of choice.

Every meter reading attempt initiated by a Meter Data Management needs to be followed by a few 'follow up' processes – also knowns as the VEE process - as listed below:

- Gap-filling attempt: to fill the data that was missed for various reasons. Using gap filling, the back-office recognizes automatically what meters have missed reporting to previous interrogations. The system then attempts to read those meters with point-to-point communication.

- Validation: the utility can set validation rules in order to validate collected data from meters. Examples of validation rules are:
    - Validation of accumulative registers against the sum of interval registers
    - Validation based on the accounts history and trend
    - Validation based on 'acceptable ranges' provided by utility based on its experience, history, and the physical acceptable ranges of values. Power Factor, for example, can only fall between 0 and 1.

- Estimation: if a piece of metering data is missing or not accepted per validation rules, the utility should be able to estimate the value. This feature is especially useful if the metering data is needed to generate bills for customers. With AMI, the frequent-data-collection has made estimating possible, the MDM or other parts of the back office can be configured based on mathematical models to estimate the missing data with a high degree of accuracy.
  The estimation models can be used to forecast future data as well. As a good use of the collected metering data, utilities should use the estimation models to forecast the total needed energy and peak demand for short-term and long-term future, in order to plan ahead for meeting future growth.

- Editing: not only can the missing data can be estimated as explained above, the existing, not acceptable data can be 'edited' toward more acceptable data as well. Mathematical calculations are used for this purpose as well.

Enough time and resources need to get dedicated for development of adapters between various systems, for example: between the head-end system and the MDM. It is recommended that regulatory bodies (e.g., DOE) or standard bodies in smart grid domain (e.g., IEEE, ANSI, UEC) establish standards and/or

requirements for various known parts of an AMI – such as head-end and MDM – so the connection between what has been made by various companies becomes more standardized.

AMI technology enables customer's participation in Demand Response programs for purpose of load reduction during peak hours therefore reducing rolling blackouts and CO2 emission and increasing grid reliability. AMI technology enables accurate remote meter reads and remote disconnect/reconnect leading to cost savings and reduction in CO2 emissions from reduction of truck rolls and field services for meter exchanges and troubleshooting. Improving the quality of service for the customers means improving their quality of life, which is the mission of a utility, and the ultimate goal of an AMI System.

10 Electric Vehicles Overview

10.1 Summary

The EV Project Team's vision is to satisfy the SGRDP goals by demonstrating EV technology and its role with regard to Smart Charging, Battery Aggregation, Microgrids, Renewables, Car/Ride Share, and Grid Impact Analysis.

The EV Project documented the above EV demonstrations, which tested the aggregation and integration of EVs with transmission and distribution systems, and assess the impact of EV integration on such systems, accounting for:

- Multiple user demographics, grid specifications, and driving patterns
- A variety of EV types
- A variety of charging equipment types

The design of the demonstration is illustrated below:

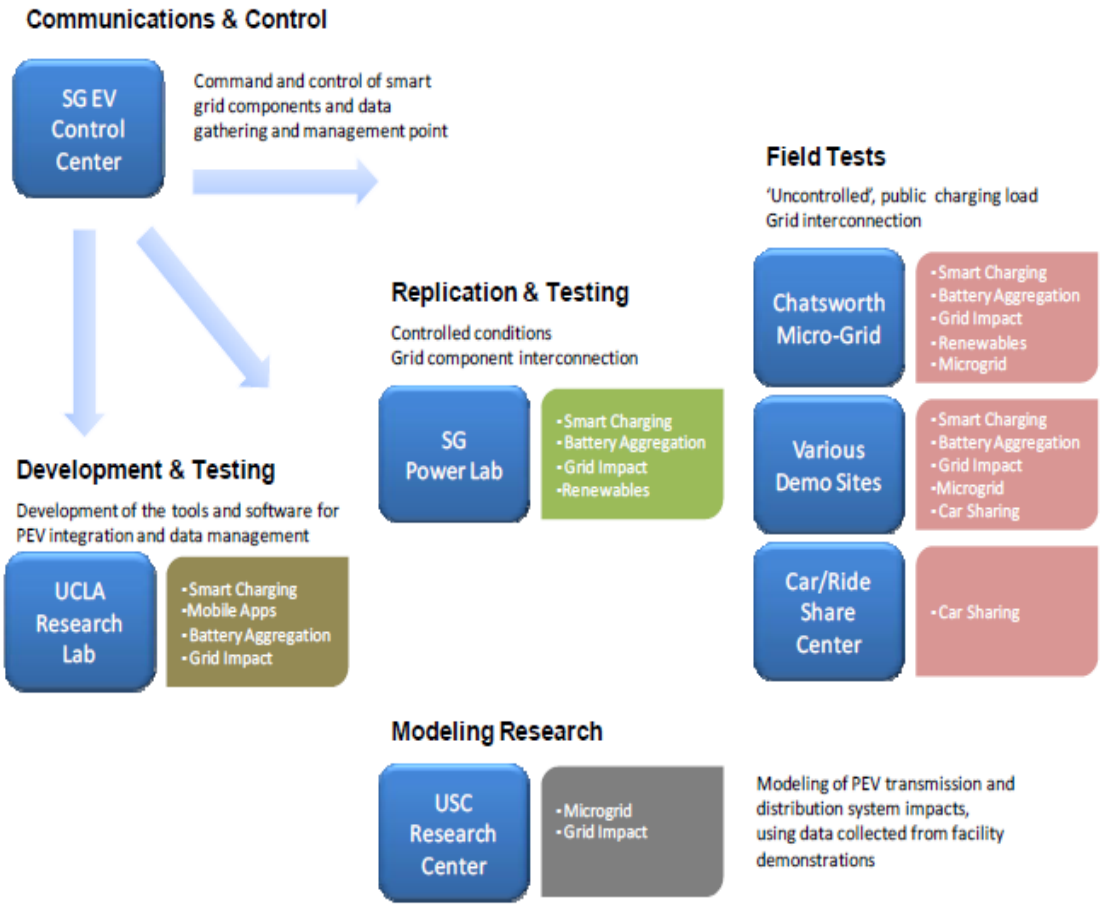


Figure 98: EV demonstration design

The project will also document experiences with the communications and control systems associated with EV integration; noting the scalability of wireless, sensing, monitoring and control within the project.

Such monitoring and control systems include the linkage between charging stations and grid management systems. The EV Project also incorporated the necessary requirements to ensure cyber security.

The EV Project Team had the following operational needs that must be satisfied by the technical implementation:

- The ability to control and monitor EV charging cycles
- The ability to collect data and analyze the effect of EVs on the electric grid
- The ability to control and monitor renewable energy sources and energy storage devices
- The ability to use the EV batteries as an energy storage device to support the grid
- The ability to have EV chargers respond to DR commands
- The ability to monitor distribution transformers
- The ability to monitor and control a sample of DA system

Overall, the project has demonstrated:

- The monitoring of chargers, power usage, and EV usage
- The viability of applying charged EVs for maintaining grid integrity related to renewable portfolio and resource planning goals
- The integration of EVs with the LADWP grid, including Smart charging, battery aggregation and backfill, renewables and EV battery integration
- The Smart-charging of EVs and charging stations in the LADWP Service Territory
- The ability of the SG infrastructure to protect the integrity of customer, configuration, and audit data

The scope of this project was to demonstrate SG and Energy Storage technologies in the LADWP service territory (specifically, LADWP SG Power Lab, UCLA Research Labs, Chatsworth substations, and EV chargers at a several different locations) and develop a suite of use cases applicable not only to the study area, but also transferable for national implementation and replication. From these use cases, the goal is to collect and provide the information necessary for customers, distributors, and generators to modify existing usage and behavior patterns to reduce system demands and costs, increase energy efficiency, increase the reliability of the grid, and optimally allocate and match resources with demand.

The anticipated social benefits of EV and energy storage utilizing SG technologies are reduced emissions, lower costs, increased reliability, greater security and flexibility to accommodate new energy technologies; including renewable, intermittent and distributed resources.

For the Electric Vehicle Project, there are six different demonstration areas that are part of the Program Objectives. These areas include smart charging, battery aggregation and backfill, a fully functional microgrid, renewables and battery integration, the use of car sharing programs at USC and UCLA and a grid impact stability/power study. Within each of these areas are use cases that will be executed in order to

satisfy the Program Objectives. In all, there are a total twenty-three use cases to successfully demonstrate in order to satisfy the objectives.

10.2 Demonstrations Key Steps

Table below lists the EV demonstrations and their key steps for completion:

SOPO	Demo/Use Case	Functions To Be Demonstrated	Key Steps
• Smart charging using WINSmartGrid for EV and existing charging stations and EV's in and around Los Angeles and the UCLA campus **• Battery aggregation and backfill** **• Fully operational microgrid. The scalability of the wireless, sensing, monitoring and control within the WINSmartGrid EV framework will be studied during the research. Scalability will be studied in the context of the UCLA Microgrid.** **• Renewables and battery integration** **Using car sharing programs at USC and UCLA**	1: Monitoring of All Chargers	Display the status of all chargers and indicate whether or not the charger is charging.	Install chargers Install meter sockets Install MDM Install AMI meters Complete Control Center Develop Software to read/control/log meter Install chargers with communication units from UCLA
	2: Reading Power Consumption for Vehicles	Monitor and store power consumption information for charging station. Real time and historical data will be collected and stored at the control center.	Install chargers Install meter sockets Install MDM Install AMI meters Complete Control Center Develop Software to read/control/log meter Install chargers with communication units from UCLA
	3: Control of Chargers	Control center will automatically manage the on/off state of charger(s) based on various conditions collected from system, charger, and EV.	Install chargers Install meter sockets Install MDM Install AMI meters Complete Control Center Develop Software to read/control/log meter Install chargers with communication units from UCLA

	4: Disconnect Vehicle that is Charging	Connect/disconnect commands will be sent from the central control centers to a specific charging station via addressable instructions.	Install chargers Install meter sockets Install MDM Install AMI meters Complete Control Center Develop Software to read/control/log meter Install chargers with communication units from UCLA
	5. Smart Charging thru Mobile Interface	Mobile devices (PDA, cell phone, & laptops) will be used to control EV battery charging and backfill operations	Install chargers with communication units from UCLA Build Server Build smartphone application Verify web interface capabilities
	6: Use of Batteries in Grid (G2V)	Charging multiple EV's at the same time with schedule determined by Control Center	Install chargers Install meter sockets Install MDM Install AMI meters Complete Control Center Develop Software to read/control/log meter Install chargers with communication units from UCLA Develop web interface

	7: Use of Batteries in Grid (G2V & V2G)	Charging & discharging multiple EV's at the same time with schedule determined by Control Center.	Install chargers with communication units from UCLA Develop web interface Purchase V2G Vehicle Test V2G Vehicle Purchase and deliver 2nd V2G Vehicle to LADWP
	8a: Distribution Effects of Battery Aggregation and Backfill (G2B)	Evaluate interaction of stationary batteries and Grid during the stationary battery charging cycles.	Install chargers Install meter sockets Install MDM Install AMI meters
	8b: Distribution Effects of Battery Aggregation and Backfill (B2V)	Evaluate interaction of stationary batteries and EV(s) during the EV(s) charging cycle.	Install chargers Install meter sockets Install MDM Install AMI meters
	8c: Distribution Effects of Battery Aggregation and Backfill (B2G)	Evaluate interaction of stationary batteries and Grid during the battery discharging cycles into the Grid.	Install chargers Install meter sockets Install MDM Install AMI meters
	9: Inductive Charging	This Use Case will demonstrate the use of inductive coupling between the charging station and EV. Additional data associated with inductive charging will be collected.	Install chargers Install meter sockets Install MDM Install AMI meters Outfit vehicle w/ Inductive Charger (DWP doing construction/testing side)

	10: Various Vehicle Charging	Monitor and compare the charging of various makes of vehicles available to the project.	Install chargers Install meter sockets Install MDM Install AMI meters Complete Control Center Develop Software to read/control/log meter
	11: Distribution Effects of EV's on the Grid	This case will demonstrate the interaction of EV(s), battery storage, and grid during the charging / discharging process. Will look at ways to manipulate the daily load profile on the grid to take full advantage of the EV(s) and battery storage.	USC Needs Data from 13
	12: Local Grid Balancing and Management	Control the power consumption of the Charging Stations to reduce circuit peaks	Install chargers Install meter sockets Install MDM Install AMI meters Complete Control Center Develop Software to read/control/log meter Install chargers with communication units from UCLA
	13: Community Storage of EV Batteries and External Storage	This case will show the interaction (charging / discharging) of EV(s) and community energy storage (CES).	Need to get from UCLA
	14: Garage of the Future	Use Case will present different methods of EV Charging (Grid, Battery, PV, and Wind).	Construct GOF

	15: Cycling of the Batteries	Case will simulate the charging and discharging of EV batteries	Developed interface to renewable source system Obtain city permit for GOF construction Validate BMS cycling capability w/ vendor (Sunverge) Construct GOF Complete Control Center Develop Software to read/control/log renewable source system
	16: Aggregation of the Batteries	This case studies the feasibility of load shedding by controlling a group of EV charging stations.	Install chargers Install meter sockets Install MDM Install AMI meters Complete Control Center Develop Software to read/control/log meter Install chargers with communication units from UCLA
	17: Integration of EV and Solar	Control Center will determine the best usage of PV energy. Options include: 1. Charge battery 2. Feed back into Grid 3. Charge EV	Developed interface to renewable source system Obtain city permit for GOF construction Construct GOF Complete Control Center Develop Software to read/control/log renewable source system

	18: Monitoring of Chargers, Power Usage, and Car Usage	Monitor and store power consumption information for charging station. Real time and historical data will be collected and stored at the control centers. Statistically analyze consumption and usage data.	copy over use case 2
	19: Distribution Effects of Car / Ride Share Program	Use Case 19 will study EV users charging habits (type of EV, time of connection, duration, consumption, and if possible utilization)	5-Year Task Outline: -Preliminary Design Field Deployment plan for chargers for Demo Sites -Start Negotiations/Design for Car/Share Program -Finalize Car Share Program -Contract with Car Share Program Company -Monitor and Evaluate Data from Ride Share Program -Documentation and reporting for Ride Share Program

	20a: Generation, Transmission, and Distribution Effects	This use case will study the effects of EV charging load manipulation has on the generation, transmission, and distribution systems. By altering charging times, can the utilization of equipment be better managed?	Use case 16
	20b: Generation, Transmission, and Distribution Effects	This use case will study the interaction of EV charging load with localized DG (solar & wind) and CES. The effects of these devices on the electrical system will be analyzed.	5-Year Task Outline: -Develop task list, lab/demo setup and budgets -Categorize LADWP Electrical Distribution System -Identify how the microgrid connects to and ties-in with the larger electric grid -Describe microgrid/grid management scenarios and potential impacts of AC and DC charging of EVs on the grid -Determine system stability impact of large scale EV deployment coupled with renewable energy -Determine the best strategy for EV charging on the electric grid -Determine impact of EV infrastructure charging on the grid in regards to system load flow, load factor, and stability

	21: Various Loading Scenarios	This Use Case will evaluate EV loading on the distribution grid. Eight different loading scenarios will be modeled and analyzed	5-Year Task Outline: -Develop task list, lab/demo setup and budgets -Categorize LADWP Electrical Distribution System -Identify how the microgrid connects to and ties-in with the larger electric grid -Describe microgrid/grid management scenarios and potential impacts of AC and DC charging of EVs on the grid -Determine system stability impact of large scale EV deployment coupled with renewable energy -Determine the best strategy for EV charging on the electric grid -Determine impact of EV infrastructure charging on the grid in regards to system load flow, load factor, and stability
	The USC team's report on best strategies for charging on the electric grid will focus on customer charging habits and the cost of peak generation. (Based on 11,19, 20b, 21)		

	The report on scalability of wireless sensing, monitoring and control network will document and analyze the UCLA EV team's research of wireless sensing scalability issues, monitoring, and control network, as implemented in the EV demonstration		

Table 65: EV demonstrations key steps

10.2.1 Garage of the Future

This use case presented different methods of EV charging. The demonstration was intended to present the following options for charge from battery, charge from grid, and charge from renewable resources such as wind and solar. This demonstration was performed in the Main Street lab facility called GoF (Garage of the Future).

Methodology

For this use case, different modes of operation at GoF were demonstrated. EV charging modes ranges from a combination of Grid, PV, and battery. The use case also demonstrated the discharging of EV, feeding back to the grid.

This demonstration used multiple resources of energy to charge the EV by having the control center send signals to SIS (Solar Integration System) to change the resource and charging sequence. V2G was followed for the feasibility of performing the discharge operations and enabled the EV team to have a consistent discharge scenario without requiring a dedicated driver to schedule and manage the driving sessions.

The demonstration was designed to have the vital data of the EV charging reported to the control center and use the Grid, Battery and PV to charge the batter, EV, or feed the grid at least once a day.

The demonstration steps are listed below:

Grid to EV

1) Run Use Case #7 for more than 1 month to collect enough data to analyze and report results
2) Review power consumption and EV data by time series (report each month)
3) Review any anomalies (Charging Stations or BMS errors) and report

Battery to EV

1) Run Use Case #8b for more than 1 month to collect enough data to analyze and report results
2) Review power consumption and EV data by time series (report each month)
3) Review any anomalies (Charging Stations or BMS errors) and report

PV to Battery / PV to EV

1) Run Use Case #17 for more than 1 month to collect enough data to analyze and report results
2) Review power consumption and EV data by time series (report each month)
3) Review any anomalies (Charging Stations or BMS errors) and report

Wind to Battery / Wind to EV

1) Run Use Case #17 (using Wind generation) for more than 1 month to collect enough data to analyze and report results
2) Review power consumption and EV data by time series (report each month)
3) Review any anomalies (Charging Stations or BMS errors) and report

Changes in demonstration design from initial steps designed are listed below.

For Grid to EV: The requirement was modified since the use case was not being demonstrated in the Garage of the Future, data was not related to GOF, power consumptions were not available; therefore the data was replaced with 1 month of data from G2V mode with availability of anomalies through SIS system logs.

Battery to EV: The demonstration was performed by USC through simulations; therefore, to cover the gap, B2V daily scenario was conducted for 1 month to provide the required data.

PV 2 Battery, PV to EV: a dedicated scenario for similar GoF operation was integrated into 1 month data collection period.

Wind2B, Wind2V: The design document required having the wind generator. However, due to unavailability of a wind turbine, this scenario has been removed from data collection operations.

The final methodology used in the demonstration is outlined below:

Grid to EV

1) Run G2V at the GoF for more than 1 month to collect enough data to analyze and report results
2) Review power consumption and EV data by time series (report each month)
3) Review any anomalies (Charging Stations or BMS errors) and report

Battery to EV

1) Run B2V at the GoF for more than 1 month to collect enough data to analyze and report results

2) Collect data from USC EV team on Use Case 8
3) Review power consumption and EV data by time series (report each month)
4) Review any anomalies (Charging Stations or BMS errors) and report

PV to Battery / PV to EV

1) Run Use Case #17 for more than 1 month to collect enough data to analyze and report results
2) Review power consumption and EV data by time series (report each month)
3) Review any anomalies (Charging Stations or BMS errors) and report

Data collection limitations include anomalies for EV and EV vitals were not available due to the limitation of the FleetCarma installation on the Mitsubishi MiEV, no access power consumption and other electrical measurements on the EV side. For more details on the methodology and data collection, refer to Use Case (Demonstration) #14 in the appendix.

Technologies Deployed

The following systems/equipment was deployed to complete the demonstration:

- AMI Meter (Net meter)
- At least 1 EV Charger
- At least 1 EV Discharger
- Solar panels, grid-tied-inverter
- Energy storage(Battery), battery charger
- Electric Vehicle
- Various electrical sensors and metering system
- Network and data flow between GoF and control center.

Success Criteria

The success criteria were to execute the final methodology steps. The EV team successfully executed the final methodology as outlined in Methodology.

Observations & Results

The demonstration was completed to have a repetitive charge/discharge of EV by various resources. It also included EV discharging during the peak hours with minimum personnel dependency. Observations found the charge rate was equivalent to 900-watt capability of the level 1 charger since the same level charger was used for all EV charging sessions. Data summary can be referred to in the appendix under Use Case #14.

Findings indicated that SIS unit was not capable of remotely avoiding PV energy usage or grid connection. The EV team had to use a manual disconnection of grid connectivity and PV connectivity to force the SIS unit to follow the schedule of charging/discharging of EV per a predefined scenario. The solar unit fed the load from available resources because it was not capable of remotely discharge and had limitation when it was configured to disconnect from the grid. Results show that the solar unit available in the market was

not feasible in having their programs manipulated and had certain mode of operations and limitations on operations.

10.2.2 Cycling of Batteries

The use case was designed to simulate EV (electric Vehicle) battery charging and discharging in the lab environment. This demonstration was performed in the Main Street lab facility called GoF.

Methodology

The planned approach was to collect data to analyze and be made available for future usage, demonstrate the operation of the solar energy resource to feed local loads, charge batteries, EVs or send to grid, and finalize the demonstration report.

For the purpose of simulating the charging and discharging of EV batteries, the control center was required to send signals to the battery management system to start testing sequence. However, the controlling of EV charge and discharge could not be performed remotely. Thus, the DWP EV team used the SIS unit battery as the scenario.

This use case required that the control center had communication to the test setup and control functions through the remote software, in addition to show that after running this use case, the batteries would work properly and control center operates as intended, have 3 to 5 charging/discharging sessions per day, report and archive vitals and status messages containing timestamps, and all batteries used here must report status and consumption to control center.

The demonstration steps were

1) BMS records EV battery vitals data
2) Vitals data sent to Control Center
3) EV Battery cycles (charging / idle / discharging) per test scenario
4) On periodic basis, BMS will report to Control Center status and charging state data

The DWP EV team used the SIS battery which was about the same size of a compact EV or half the size of standard EV (11 kWh). Approximately 35-50 miles of driving per cycle was saved by substituting EV driving with SIS battery discharge, which saved about 100-150 miles of daily driving to satisfy the use case. The modified scenario was scheduled to run through the SIS web interface and the vitals of battery and data were available through the SIS archive.

Technologies Deployed

The following systems/equipment was deployed for this demonstration:

- AMI Meter (Net meter)
- At least 1 EV Charger (replaced due to modification of use case flow)
- Energy storage(Battery), battery charger
- Electric Vehicle (replaced due to modification of use case flow)
- Various electrical sensors and metering system

- Network and data flow between GoF and control center.

Success Criteria

The success criteria were to execute the demonstration steps as listed in Methodology. The EV team successfully executed the steps.

Observations & Results

Findings show the internal temperature of the batteries increased from charge and discharge. The results of the demonstration were recorded and archived. The demonstration was designed to have the cycling of batteries scheduled to run 3 times a day with 1 hour standby between each interval on the EV, but due to limitations as mentioned in methodology, it was modified to cycle the available battery resource at the SIS unit. The expected results and data were collected.

Results indicated that the SIS unit provided a platform suitable for programming and scheduling a renewable energy resource along with grid connection and storage (battery) resource. The modification on the use case to use the SIS battery instead of EV battery enabled the achievement of the data collection target, as well as saved time and resources. Operators were able to set conditions on top of schedules and incorporated a flexible on-demand ruleset for the scenario resulting from using the SIS unit.

The planned impacts and benefit for this demonstration was to use the collected data in overall distribution system planning, asset management, infrastructure optimization, and evaluation of cost effectiveness. Since only collected data from SIS was available, this use case impacted the view of EV usage, especially battery EV charging scenario using level 1 charger. For more information on results and data collection, refer to Appendix AM.

10.2.3 Integration of Electric Vehicle (EV) and Solar

This use case was designed to apply the best usage of PV energy. Options include: charge battery, feed back into grid, and charge EV. DWP EV team and UCLA EV team performed their own demonstrations.

Methodology

For this use case, DWP EV team assumed the highest priority for the use of Photovoltaic (PV) energy is to have the SIS battery charged, then have the EV as the second priority. It was assumed that the EV was leaving the charging station every day at around 2:30pm and there is a spike in demand at 4pm that will discharge the battery between 4-5 pm with maximum available power.

The DWP EV Project team installed various equipment at the Garage of the future (GOF) in order to demonstrate solar to grid (PV2G), solar to battery (PV2B) and solar to EV (PV2EV) operations. To resolving the issue where battery backfill may not be possible without modifying the BMS (Battery Management System) and other circuits on the EV, a Mitsubishi (iMiEV) was selected as the EV and a dedicated V2G circuit is design by UCLA team to make the (grid tied) vehicle to grid energy transfer possible.

The DWP EV project team was responsible for collecting the available data from EV, Solar, and Grid. The scenario should have 1 PC session per day and multiple connections to the grid, battery and EV during the session and the operation was performed for about 1 month (8/21/2015-9/24/2015). The demonstration required having a control center with the ability to control the assets such as PV and battery, as well as a communication method to send commands and collect and archive data. The objective was to show the PV would work properly, the control center operated as planned, and the data, such as the vital, consumption, and status messages with timestamps were to be archived and reported.

During the data collection period, available measurements in GoF were collected, which included data from the solar unit and AMI meters. The following data from the solar unit and AMI meter was collected from each of the scenarios listed below: current, voltage, real and reactive power, frequency, etc.

- Solar unit sending energy to grid; when there is excess energy available at GoF and both battery and EV are charged and no additional load exists in the Garage (solar to grid (PV2G)).
- Solar unit is charging Battery; this is the highest priority at GoF to have a reliable energy source capable of use for loads, EVs or feeding back to grid.
- Solar unit charging the EV; when there is no need for charging Battery unit at GoF.

The planned approach on the demonstration was to analyze the collected data to be available for later usage, demonstrate the operation of the solar energy resource to feed local loads, charging batteries, EVs or sending to grid, and finalize the demonstration report. Option 2 was selected out of the 3 options listed below. Since the goal of the use case was to have the battery charged at maximum usage of PV energy and to collect the most possible vitals, option 1 was not a reasonable task since it required a dedicated driver to drive for approximately 62 miles to discharge the battery and option 3 was not recommended since the team already had a battery charge and discharge use case, the team could not use the same battery.

- **Option 1:** To discharge the EV a dedicated driver would be required to drive the EV every day for the duration of this use case. The specs of i-MiEV require the vehicle to be driven approximately 62 miles to discharge the battery, which is not a reasonable daily operational task.
- **Option 2:** Can be a replacement for method 1, because there is no need to drive the EV as the EV can be discharged by sending the energy back into the grid. Method 2 also has some limitations on connecting and disconnecting the charge and discharge cable, which needs to be done by a locally available operator.
- **Option 3,** is not recommended due to its unrealistic nature, and since we already have battery charge and discharge in this use case, we cannot use the same battery as the EV.

Option 2 had limitation on connecting and disconnecting the charge and discharge cable. The locally available operator was assigned to do so to complete the demonstration. The EV was scheduled to charge and discharge by locally available personnel at GoF once in the morning and once in the afternoon for 5 working days of a week (Mon-Fri). This use case had a limitation in not being able to disconnect from the grid automatically based on the trigger on the system, so it was not possible to enforce stop feed from the grid to the load.

The UCLA EV team also took park to research and determine the best usage of PV energy by exploring different options for determining the best usage were charging the battery, feeding back into grid, and charging EVs by using their WINSmartEV infrastructure and installing a power meter on an existing inverter of a photovoltaic array on the rooftop of the buildings on UCLA campus.

The methodology outlined below was executed by UCLA EV team in order to complete the use case.

A. PV to Grid

1) Control Center send signal to connect PV to Grid
2) Periodically, Control Center collects PV Vitals
3) PV stops generating energy
4) Control Center accumulates and archives PV Vitals data

B. PV to Battery

1) Control Center send signal to connect PV to CES
2) CES receives signal from Control Center to charge
3) CES records CES vitals
4) CES vitals sent to Control Center
5) On periodic basis, CES & PV report to Control Center status and accumulative charging data
6) CES informs Control Center charging is complete
7) Control Center sends signal to connect PV to Grid
8) CES reports results of charge to Control Center

C. PV to EV

1) Charging Station records EV Vitals
2) Charging Station records Scenario Data
3) EV Vitals & Scenario Data sent to Control Center
4) Control Center send signal to connect PV to Charging Station
5) PV collects & sends Vitals to Control Center
6) Control Center sends commands to Charging Station (to charge using PV energy)
7) On periodic basis, PV will report to Control Center status and accumulative energy data
8) On periodic basis, EV will report to Control Center status and accumulative charging data
9) EV informs Control Center charging is complete
10) Control Center sends signal to connect PV to Grid.
11) PV reports results to Control Center
12) EV reports results of charge to Control Center

The EV Project team installed solar panels as a distributed energy source and they were equipped with an energy management system that was able to communicate back to the SG EV Control Center. SG EV Control Center determines how to use the energy collected from the solar panels. The UCLA EV team performed the demonstration at the SG Power Lab, the SG EV Control Center and Various Demo Sites.

Technologies Deployed

List of systems/equipment deployed at GoF for this use case includes

- AMI Meter (Net meter)
- 1 EV Charger
- Solar panels, grid-tied-inverter,
- Energy storage(Battery), battery charger
- Electric Vehicle
- Various electrical sensors and metering system
- Network and data flow between GoF and control center

List of systems/equipment deployed at UCLA for this use case

- Super Control Center
- EV Control Center
- PV Array
- 136 EV Chargers
- Battery Energy Storage System
- Electric Vehicles

Success Criteria

Description of success criteria along with the status of the criteria for this Demo at GoF are listed below. The collected data for EV was cut due to the unavailability of internal EV data access; thus the solar point of connection data was considered as EV data.

1. Develop a complete solar, EV, Grid, Battery system **-Completed**
2. Test and demonstrate PV2G, PV2B, and PV2EV strategy using developed system **-Completed**
3. Deploy/Install specified equipment **-Completed**
4. Using actual system to test the solar power flow strategy **-Completed**
5. Report collected data**-Completed**
6. Network and data flow between GoF and control center. **- Completed**

The description of success criteria for demonstration at UCLA were listed in methodology and were completed by UCLA EV team.

Observations & Results

DWP EV team found sending PV energy into the grid is usually smoothed by storing the produced transient energy in local battery and sending a non-variable power rate to the grid. In DWP EV team's system, the step of power flow from PV to the grid was 100W, which indicates power variations due to changes in solar radiation would be increased or decreased in increments of 100W and the variations which were less than 100W would be stored in the local battery.

Observations showed the solar unit cannot disconnect the grid remotely and cannot stop the feed to the load, acting like an uninterruptible power source. This modified use case helped the grid during the peak by battery with the least dependency on personnel for operation support. More reference and data collection summary is available in Appendix AN.

The UCLA EV team found the system deployed at UCLA versatile as it allowed additional resources to join and displayed relative information. The Super Control Center was able to implement a wide range of scheduling algorithms and they could be defined by users and managed the macroscopic scale of the energy management while leaving the microscopic management role to the local EV control centers. The scalability of the system was tested with Virtual Devices.

UCLA had to utilize an existing PV array due to delays in the contraction of a photovoltaic array system. Data collection summary from UCLA's demonstration can be referred to in Appendix AK.

10.2.4 Battery Aggregation and Backfill

This demonstration was designed to evaluate the interactions of stationary batteries and Grid during the stationary battery charging cycle, stationary batteries and EV(s) during the EV(s) charging cycle, and stationary batteries and Grid during the battery discharging cycles into the Grid. The UCLA EV team was responsible for exploring of the feasibility of load-shedding using a group of EV chargers.

Methodology

The following assumptions were made by USC EV team for use case 8:

- In the approach, the USC EV team assumed the average power at 5 kW per house. IEEE 34 Bus has total power of 2 MW, which leads to 400 houses as the loads along IEEE 34 Bus System. Assume that level 2 charging has capacity of 8 kW (32A) at 240V with 6 hours to be fully charged.
- People will drive to work from 6-8 AM during which they can neither charge from the grid nor feed to the grid.
- People will drive back home from 5-8 PM during which they can neither charge from the grid nor feed to the grid.
- Before driving to work (6AM) and back home (8PM), people will have their EVs fully charged at 100% battery.
- Each trip, from home to work place, or from work place to home will use about 50% of the electricity, which is equivalent to 50% remaining battery.
- People will not use their EVs during work hours, from 8AM to 5PM.
- As soon as people arrived at work place or home, they will plug in their EVs ready for G2V or V2G.

In use case 16 performed by UCLA EV team, they used their WINSmartEV infrastructure, sent demand response signals to the EV Control Center through the Super Control Center and monitored and collected data during a load-shedding event.

The EV Project team installed appropriate grid-tie inverters and bi-directional AMI smart meters at certain charging stations to demonstrate Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) operations. Varied by

the make and model of the EV, battery backfill may not be possible without modifying the BMS and other circuits on the EV. The EV Project team studied and investigated a non-destructive approach to implement this demonstration. All EVs that participated in the V2G demonstration may need to be equipped with additional circuits and modules.

The UCLA EV team was able to obtain the power consumption information on parking structure level through interaction with EV control center with WINSmartEV Infrastructure in lieu of collecting power consumption information from each individual EV charger. The demonstration faced the challenge of obtaining Status of Charger which prevented the collection of the SOC regularly from connected EVs. Based on the mentioned developments, the demonstration on the use of batteries in the grid was modified as outlined below.

1) Vehicle operator plug in the vehicle when arrived at the charging station
2) Vehicle operator use mobile application to activate a charging station
3) Control Center records initial Charging Record (starting status)
4) Control Center sends commands to Charging Station to activate the charger
5) Charging Station charges EV with appropriate current based on charging scheduling algorithm
6) On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
7) Control Center detects very little current are being drawn by the EV
8) Control Center records final Charging Record (ending status)
9) Control Center sends commands to end the charging session
10) Control Center informs vehicle operator results of charging session
11) Control Center resets the Charging Station for new charging session

Data was collected from the project batteries during the charging and discharging cycles. Current, voltage, real and reactive power, frequency and harmonic data from the charging stations were used to model power flows on the distribution system for each of the scenarios. For analysis on the distribution system, refer to USC EV TPR Use Case #8 in the appendices for details.

The UCLA EV team was able to demonstrate the collection of aggregated EV power consumption and observed the EV charging load peak demand for potential demand response program by utilizing Super Control Center's data aggregation approach to interact with EV Control Center in UCLA WINSmart Infrastructure.

To complete the demonstration on the use of batteries in grid for 2-way charging, the UCLA EV team used their WINSmart EV infrastructure and developed the Mitsubishi i-MiEV Power Box to support V2G capabilities since EVs did not have V2G capabilities. The EV Project team installed appropriate grid-tie inverters and bi-directional AMI Smart meters at designated charging stations to demonstration V2G and G2V operations.

The 2-way charging demonstration took into account the power source/sink management optimization. The EV Project team performed simulations in a controlled environment to implement the optimization control performed on EVs where energy was flowing back into the electrical grid. To ensure the EV battery did not sustain any damage due to charging, 15 minute interval data was collected.

The design of the demonstration was changed as outlined below due to the lack of the V2G technologies:

Planned Methodology	Final Used Methodology
1. Charging Station records EV Vitals	1. Charging Station records Scenario Data
2. Charging Station records Scenario Data	2. Charging Station records Session Parameters collected from EV operator
3. Charging Station records session parameters collected from EV operator	3. Scenario Data, & Session Parameters sent to Control Center
4. EV Vitals, Scenario Data, & session parameters sent to Control Center	4. V2G Control Center process all data received
5. Control Center process all data received	5. V2G Control Center sends commands to Charging Station to charge & discharge EV batteries per Session Parameters automatically
6. Control Center sends commands to Charging Station to charge & discharge EV batteries per session parameters	6. Charging Station charges/discharges EV per commands received
7. Charging Station charges/discharges EV per commands received	7. On a periodic basis, Charging Station will report to V2G Control Center status and accumulative charging data
8. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data	8. EV operator stop charging/discharging operation
9. EV informs Station charging is complete	9. Charging Station reports results of charge/discharging to V2G Control Center
10. Charging Station reports results of charge to Control Center	10. EV Operator removes & stores Charging Cable and V2G equipment
11. Charging Station inform operator results of charging session	11. Charging Station resets for new charging session
12. EV Operator removes & stores Charging Cable	
13. Charging Station resets for new charging session	

Table 66: EV Team's Planned vs. Final Used Methodology - Battery Aggregation and Backfill

The UCLA EV team had to retrofit a vehicle to complete the 2-way charging demonstration.

In the use case of aggregation of batteries, UCLA executed the final methodology shown below with the initial planned methodology. The approach of the use case was modified to achieve monitoring and controlling of groups of aggregated EV chargers, a flexible platform with hierarchical infrastructure was required.

Planned Methodology	Final Used Methodology
1. Charging Stations records EV Vitals	1. A demand response event is manually triggered through SCC interface
2. Charging Stations records Scenario Data	2. The SCC operator chooses the parking structure to shed EV charging load.
3. EV Vitals & Scenario Data sent to Control Center	3. Load Shedding command is sent to EV control Center
4. Control Center sends commands to Charging Stations	4. EV Control Center determines how much load can be reduced based on current EV charging load.
5. Charging Stations charges EV per commands	5. EV Control Center sends commands to Charging Stations
6. On periodic basis, Charging Stations will report to Control Center status and accumulative charging data	6. On periodic basis, Charging Stations will report to Control Center status and accumulative charging data
7. EVs inform Stations charging is complete	7. Aggregated EV charging information is sent to SCC.
8. Charging Stations reports results of charge to Control Center	8. SCC operator observe load shedding on SCC
9. Charging Stations inform operator results of charging session	9. Demand response event is completed.
10. EV Operator removes & stores Charging Cable	10. SCC sends command to EV control center to end load shedding event.
11. Charging Stations resets for new charging session	11. EV control center sends command to each individual charger to resume original charging power
	12. SCC operator observes EV charging load return to normal.
	13. Demonstrate load shedding and produce an outcome report describing the optimal aggregation, control methods, and potential benefit analysis

Table 67: UCLA EV Team's Planned vs. Final Used Methodology - Battery Aggregation and Backfill

Technologies Deployed

These two systems were deployed as distribution network models that were selected to compare with the benchmark results and have a more reliable analysis for the Chatsworth system:

- An Institute of Electrical and Electronics Engineers(IEEE) 34 bus test system reflecting an industry standard distribution test model
- A Chatsworth Distribution System or microgrid representing a residential/industrial area in the LADWP system with a special focus to the circuit numbers 22 and 23

The UCLA EV team deployed the Super Control Center, EV Control Center, 137 EV chargers, and EVs to complete use case 6 (Use of Batteries in the Grid (G2V only) and use case 16 (aggregation of the batteries). The Super Control and EV Control Center were also deployed as part of the demonstration of use case 7, along with Mitsubishi i-MiEV grid tied inverter (discharge interface), and Mitsubishi i-MiEV.

Success Criteria

Description of success criteria and status for this USC's use case 8 are listed below:

1) Develop models of Chatsworth using Electrical Distribution Design (EDD - power system analysis and simulation software) (Completed)
2) Test G2V, G2B, B2V, B2G and V2G strategy using EDD model (Completed)
3) Use mathematical modeling and analysis tool MATLAB and Microsoft Excel to model and analyze various charging and discharging strategies associated with EV, CES, PV, and the Grid (Completed)
4) Use PSCAD to model high-frequency transients to assess the harmonic impact of multiple EV chargers on the electric network (Completed)
5) Using actual system data to test the charging/discharging strategy. This criteria was reduced due the reduction in the anticipated EV penetration in Chatsworth. This impacted in the scope of test case of item (6) (Demonstration cannot be completed due to lack of data)
6) Calculate the five indices (Utilization factor, Capacity factor, Load factor, Power factor, and Power quality) for circuits 88—22 and 88-23 (Completed)

The UCLA EV team fulfilled the success criteria for use case 6, 7, and 16 by completing the activities outlined in Methodology.

Observations & Results

The observations from the simulation studies found the relationship between number of EV and power change is very linear which can be used to predict the power needed when more EVs are in the system. Reactive power will increase dramatically after the Battery Storage and EVs are plugged in, which will cause problems related to voltage stability in power grid. Additional observation showed battery storage will generate higher harmonics when compared to no battery storage in the system which may damage the system and devices. However, the harmonics are much lower compared with PV system. Additional observations can be referenced in the appendices in Technology Performance Report Use Case (Demonstration) #8.

The UCLA EV team found most of the workplace charging had most of the EV charging load during week day from the Weekly EV Charging Load profile. Based on the Daily EV charging Load profile, the UCLA EV team found most of the people started their charging sessions in the morning and completed their charging in the early afternoon. The level 3 chargers at UCLA parking structure 4 was the dominant EV Charging load out of all the EV charging stations on campus. For more details, including data collection summary on the use case performed by UCLA, refer to UCLA TPR use case 6 in the appendices.

In the 2-way charging use case implemented two scenarios. In one implementation, the control center made a decision on charging/discharging schedules and sent out control signal automatically based on time-of-use price variation. The UCLA EV team saw the estimation on energy consumption and cost for the

completion of charge were not the same as the actual value, but had high accuracy that could be used as a good indicator for users. The discrepancy in value was due to system delay and EV charging/discharging change of status delay.

In the alternative operation, it focused on manual control of EV's charging status since it would be probable for certain users to manually discharge their EVs from charging or vice versa. Manual operation would be a backup alternative from the automatic operation. G2V or V2G could be switched off manually when errors occur in the automatic operation.

The V2G operation was tested and found the best current level would be 5A in order to keep the system stable. When the current goes up to 8 to 9 A, there was a higher probability of tripping off the system due to the protection scheme on the EV; this issue could not be resolved due to the inability to access the vehicle SOC. Refer to the UCLA TPR EV use case 7 in the appendices for data collection summary.

Based on the EDD, Matrix Laboratory (MATLAB) and PSCAD simulation studies, we found that the interaction of EVs, CES, and grid during the charging/discharging could have great impact on the power grid. The key point of these strategies are managing peak load condition with EVs discharging to the grid to save electricity usage and shave the peak of the load curve. Results suggested that commercialized EV benefits for the better future of developing EVs industry. Smart charging (G2V) for the purpose of "valley-filling" and V2G are very effective charging options compared to others. The harmonic test is largely based on how the models are built. Different EV models may also take us to different outcomes. Thus, all the conclusions in this paper can only be regarded as a reference. Practice is the sole criterion for testing truth.

The 2-way charging demonstration had inefficiency caused by the multiple layers of power electronic device introduced in the process. The total energy loss after each layer of power electronic device was visible when the UCLA EV team used the industry standard solution in power electronic; the issue originated from the charge to move (CHAdeMO) protocol. Since it was a proprietary protocol, it could not directly use an inverter to receive power from the EV. Although the Mitsubishi Power Box was implemented, it was not grid tied, so it required additional layers of power electronics.

The planned impact and benefit for 2-way charging were to show how utilities and customers will be able to utilize the V2G technology to cut cost by using EVs to help reduce peak demand; however, due to lack of V2G technology commercial availability to the public, the planned impact and benefit was not realized.

In the study of aggregation of batteries, UCLA EV team found the following advantage for the developed system – ease of integration with various types of end devices, allow group management on EV charging stations from having multiple layers of authentication and privileges, and ability to manage complex scheduling algorithm to control individual charging plug from the EV control center. Data collection summary can be found in the appendix under UCLA TPR EV Use Case 16. Results pointed out that problems may occur if the communication network is not proficient as the infrastructure requires a reliable communication network. The UCLA EV team was able to shed approximately 28 kW during a load shedding event, which supported the planned impact and benefits for this demonstration by using EV batteries to provide a utility with the ability to reduce peak demand, prevent blackouts/brownouts, which can save money.

10.2.5 Distribution Effects of EV's on the Grid

This demonstration was designed to evaluate the interaction of EV(s), battery storage, and grid during the charging/discharging process and look at to modify the daily load profile on the grid to take full advantage of the EV(s) and battery storage.

The USC team studied the fully functional Microgrid which included installed and operating EV chargers. Various positive and negative effects on the Microgrid such as: power quality issues (over-voltage, voltage sags, switching surges, harmonics and noise), impact on distribution infrastructure (transformers, wires, cables, and capacitors), capacity factor, utilization factor, load factor, system reliability, asset management, infrastructure optimization, cost effectiveness, and minimizing electric utility costs were analyzed in the study.

Methodology

The fully functional Microgrid used in the demonstration provided the opportunity to study larger grid impacts in a controlled environment and test the impacts of electric vehicles on the future grid. Data collected from LADWP Substations, Distribution Automation equipment, and AMI meters were used in the demonstrations.

One of the objectives in the demonstration was to show how customers can lower their demand charges or limit their daily electric loads with EV chargers and battery storage. The demonstration took place at the SG Power Lab, various demonstration sites, and the SG EV Control Center.

The demonstration ran for more than a week to collect enough data to analyze and create a process to control charging/discharging cycles. The power consumption by time series was reviewed and reported each week during the use case along with the EV data by time series. Charging stations or battery errors were also reviewed and reported.

To enable analysis of EV distribution effects, three sets of distribution network models were selected as listed below:

1) An IEEE 34 bus test system reflecting an industry standard distribution test model
2) A USC distribution network or microgrid reflecting a large urban complex in the LADWP system
3) A Chatsworth Distribution System or microgrid representing a residential/industrial area in the LADWP system with a special focus to the circuit numbers 22 and 23

Four software programs listed below were used to develop those models:

1) Distribution system modeling software Distribution Engineering Workstation (DEW) by Electrical Distribution Design, Inc. (EDD) was used to model the distribution network
2) Power system distribution simulator software OpenDSS by Electric Power Research Institute (EPRI) was used to model the distribution networks

3) Designing distributed generation (DG) systems software Hybrid Optimization Model for Electric Renewables (HOMER) by National Renewable Energy Laboratory was used to evaluate the economic and technical feasibility of a large number of technology options and to account for variations in technology costs and energy resource availability
4) A multi-paradigm numerical computing environment and fourth-generation programming software MATLAB by Mathworks was used to develop an Utility-Customer Interface Strategy and User Application for Electric Vehicles and Distributed Generation Management

Attachment of multiple EV-charger loads of various classifications was enabled by the EDD models on the three system representations and OpenDSS models on the two system representations. They were designed to show the aggregate effect of the multiple EV-charger loads at substation connections to the transmission grid.

A customer interface and user application was created for electric vehicles and distributed generation management which enabled the achievement of goal of load interruption during peak demands and load shifting of EV chargers whenever feasible.

Technologies Deployed

An IEEE 34 bus test system reflecting an industry standard distribution test model, a USC distribution network or microgrid reflecting a large urban complex in the LADWP system, and a Chatsworth Distribution System or microgrid representing a residential/industrial area in the LADWP system with a special focus to the circuit numbers 22 and 23 were deployed along with the following software and models:

- EDD: IEEE 34, USC, Chatswort
- OpenDSS: IEEE 34, USC
- HOMER: USC Microgrid design and operation
- MATLAB: Utility-Customer Interface and user application for EV and DG management

Success Criteria

Description of success criteria and status for this demonstration are listed below:

1) Develop models of Chatsworth (as well as IEEE and USC) using EDD (as well as OpenDSS, and HOMER) (completed)
2) Test the interaction of EV(s), battery storage, and grid during the charging / discharging process using EDD model (completed)
3) Test USC microgrids using PSS/E model (completed)
4) Deploy/Install specified equipment (this was not completed since the equipment deployment was reduced due to the reduction in the anticipated EV penetration in Chatsworth).
5) Demonstrate the interaction of EV(s), battery storage, and grid during the charging / discharging process (completed)
6) Deploy a utility - customer interface strategy and user application for electric vehicles and distributed generation management (completed)

7) Demonstrate actual Chatsworth microgrid – (was not completed since the microgrid applications that required facility enhancements were not implemented for the Chatsworth system).

Observations

Observations were based on simulation studies since equipment was not deployed in time to have approximately one year of data to conduct the actual system demonstration. The modeling and the testing of the Chatsworth were successfully completed. Data collection summary and reports published for this demonstration can be referenced in Appendix V.

Results

The study determined the cost of an islanded mode microgrid is larger compared to a grid considered as an energy supply. The fuel cost of microturbines natural gas is more expensive than the cost energy provided by the LADWP. While microturbines have lower capital cost, it has a very high fuel cost in each scenario simulated. PV panels have the highest capital cost while solar panels life time span is longer than microturbines by 25 years.

The study illustrated that without a microgrid is the most economically optimal than replacing the existing system. Aside from the cost, a microgrid will add reliability and security to the campus electrical demand and provide environmental advantages. This study identified the most optimal microgrid plan consists of a combination of microturbines, PVs, batteries, inverters, and the main grid (LADWP).

10.2.6 Monitoring of Chargers, Power Usage, and Car Usage

This demonstration was completed on charging station and electric vehicle usage in Los Angeles, CA. The study evaluated the data from large corporate fleet, local residential EV, and LADWP ride share EV. The charging patterns and usage of EV and charging stations were recorded from LADWP and UCLA station records and were analyzed for results to provide insights for utility companies for resource planning and future installation of wired and wireless charging EV infrastructures.

Methodology

LADWP purchased more than fifty EVs to be utilized in the fleet for the Car/Ride Share Center (used for daily activities by personnel) to demonstrate the distribution effects of the EV Car/Ride Share program, and the various Smart Charging demonstrations. To accommodate for the new EV's charging standards, the existing EV charging infrastructure was retrofitted. The program included addition to parking spaces, signage, and EVs to the existing LADWP fleet.

During the demonstration, EV charging start time, duration, energy, and other charging information was collected from each charging.

The program collected charging data through meters or FleetCarma (third party). Miles driven between charging sessions were collected for statistical analysis and EV driving characterization. Analysis was

performed to investigate the feasibility of using EV chargers to reduce peaks and valley on the load curve once enough power consumption data was collected to determine usage patterns and load curve shapes.

Data was collected for more than 1 year from UCLA and LADWP. Power consumption and EV data by time series was reviewed and reported each quarter. No data was collected from charging stations for local public use since there was no capability to do so in during that time period. Details on tasks executed by USC per scenario can be referenced in Appendix W.

UCLA EV team used their WINSmartEV infrastructure to monitor and collect data from all of the EV charges at the UCLA campus. The platform consists of a control center, mesh communication network, and the controllable Electric Vehicle Supply Equipment. The EV team was not able to obtain detailed user data and fully control the charging operations from the control center since most charging stations used proprietary communication protocols. Therefore, the UCLA EV team designed and developed an open-architecture charging station that supported the data collection and circuit control for the project.

UCLA developed bi-directional communications between the Electric Vehicle Supply Equipment and the Control Center, supported different power information signal formats, performed test procedures every 15 minutes or less, monitored and evaluated data from all EV chargers. For more details on the demonstration performed by UCLA for this use case, refer to Appendix Z.

For the demonstration on reading power consumption for vehicles connected to chargers, the SG EV Control Center used software to check the eligibility of the connected EV's and user profiles to authorize the EV for charging. The SG control center collected the charger/AMI ID, connection time stamp, voltage and current, and kW from EVs and chargers. The following set of data was not available for collection because they are typically hidden behind the EV BMS system.

- EV battery voltage
- EV battery current
- EV battery temperature
- BMS error message

Limitations found was on the state of charge data, which was only available for Nissan Leaf, were:

- The SOC modules were a non-standard solution so the official information on the format of the SOC data was currently not available
- The SOC data format on the CAN bus was subject to change by the EV manufacturer
- It was challenging for an average user to use the SOC modules to transmit the SOC data from the EV
- Creation of additional SOC modules was limited
- The TI ZigBee modules that were used for SOC application were no longer in production
- SOC data communication contained faulty data and contained errors

Independent from the Nissan Leaf, UCLA SMERC adopted an alternative approach to estimate SOC and scenario data was also collected independently. Details can be viewed in Appendix AA. The alternative approaches directed UCLA to change demonstration steps to:

1) Vehicle operators plug in the vehicle when arrived at the charging station
2) Vehicle operators use mobile application to activate a charging station
3) Control Center records initial Charging Record (starting status)
4) Control Center sends commands to Charging Station to activate the charger
5) Charging Station charges EV per commands
6) On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
7) Control Center detects very low current are being drawn by the EV
8) Control Center records final Charging Record (ending status)
9) Control Center sends commands to end the charging session
10) Control Center informs vehicle operator results of charging session
11) Control Center resets the Charging Station for new charging session

Technologies Deployed

The following systems/equipment were deployed for this demonstration:

- AMI meters Customers for Residential, Commercial, and Industrial
- EV
- More than 1000 EV chargers were installed.
- FleetCarma was installed in the newly purchased EVs added to LADWP's fleet.
- Super Control Center
- EV Control Center

Success Criteria

Description of success criteria and status for this demonstration on Charging Station Usage, Power Usage and Car Usage of large corporate fleet at LADWP are listed below:

1) LADWP assigned EV fleet and charger overview (completed)
2) Charging patterns of all assigned EVs in LADWP from May 2015 to May 2016 (completed)
3) Charging station usage and power usage in LADWP for assigned EVs from May 2015 to May 2016 (completed)
4) Load curve prediction in California using LADWP assigned EV data (completed)

Description of success criteria and status for this demonstration on Charging Station Usage, Power Usage and Car Usage of large corporate fleet at UCLA are listed below:

1) UCLA fleet and charger overview (completed)
2) Charging patterns of all EVs in LADWP from July 2014 to August 2015 (completed)
3) Charging station usage and power usage in LADWP from July 2014 to June 2015 (completed)
4) Load curve prediction in California using UCLA data (completed)

Description of success criteria and status for this demonstration on Charging Station Usage, Power Usage and Car Usage in LADWP local residential area are listed below:

1) LADWP residential charger overview (completed)
2) Charging patterns of all residential EVs in LADWP service territory from February 1st to April 30th 2016 (completed)
3) Charging station usage and power usage in LADWP for residential EVs within LADWP service territory from February 1st to April 30th 2016 (completed)

Description of success criteria and status for this demonstration on Charging Station Usage, Power Usage and Car Usage of LADWP ride share are listed below:

1) LADWP ride share fleet and charger overview (completed)
2) Charging patterns of all carpool EVs in LADWP from May 2015 to May 2016 (completed)
3) Charging station usage and power usage in LADWP for carpool EVs from May 2015 to May 2016 (completed)
4) Load curve prediction in California using LADWP carpool data (completed)

UCLA successfully completed the following success criteria on the monitoring of all chargers:

- Control Center sends station status request
- Station receives status request command from Control Center
- Station sends back to Control Center, status message
- On a periodic basis, Charging Station will report to Control Center status and accumulative charging data

UCLA successfully completed the following success criteria on Reading Power Consumption for Vehicles Connected to Chargers:

- Vehicle operators plug in the vehicle when arrived at the charging station
- Vehicle operators use mobile application to activate a charging station
- Control Center records initial Charging Record (starting status)
- Control Center sends commands to Charging Station to activate the charger
- Charging Station charges EV per commands
- On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
- Control Center detects very low current are being drawn by the EV
- Control Center records final Charging Record (ending status)
- Control Center sends commands to end the charging session
- Control Center informs vehicle operator results of charging session
- Control Center resets the Charging Station for new charging session

Observations

In LADWP fleet and charging station, EV charging events were recorded from 5/20/15 – 5/20/16 where energy transferred for 3,073 charging events were studied. Energy distribution were charted from charging station usage and analyzed daily, monthly, seasonally, and annually.

In the study on UCLA fleet and charging station, EV charging events were recorded from 6/1/14-8/31/15. Energy distribution were charted from charging station usage and analyzed daily, monthly, quarterly, and annually.

In the study on residential EV and associated charging stations, EV rebate meter were installed and each meter represented 1 home where data was recorded from 2/1/16 - 4/30/16. Meters were recorded and updated the chargers' data in 15 minute intervals, which provided more than 1 million record of data from 223 rebate meters.

EV charging events were recorded from 5/1/15 - 5/20/16 from the LADWP ride share EV program and associated charging stations. Energy distribution were charted from charging station usage and analyzed daily, monthly, seasonally, and annually.

The statistic results from each case of studies were used to provide information and practical insights for utility companies to make city planning and future installations of EV charging infrastructure. For more analysis on data collected, refer to Appendix W.

UCLA EV team collected 5 months of data from level 1 and level 2 EV chargers. The collected data included the name, timestamp, voltage, current, frequency, power factor, active power, apparent power, and main energy. UCLA EV team also collected 5 months of data from a level 3 EV charger for the time, voltage, current, total main energy, and total active power. Details on data collected can be referred to Appendix Z.

Observations from UCLA demonstration the Reading Power Consumption for Vehicles Connected to Chargers showed different parking infrastructure areas showed the different charging behaviors. Most EV charging energy consumption occurred at UCLA, followed by Sunset Village Fleet and Santa Monica. The highest average consumption occurred in Santa Monica (users stayed longer and consumed more power per session). Data collection summary can be viewed in Appendix AA.

Results

The results from LADWP fleet and charging station showed that 90% of charging events transferred less than 11 kWh and 94% of the time EV was connected for less than 4 hours during plug-in time. Based on the charging status usages, results showed it is possible to use EV chargers to balance load curve shapes. Most of the energy delivered from charging stations occurred during daytime, which can be offset by installing PV panels.

The results from UCLA fleet and charging station showed that 90% of charging events transferred less than 12 kWh and 67% of the time EV was connected for less than 4 hours during plug-in time. The USC EV team was able to conclude that it's feasible to use EV chargers to balance load profiles by removing or reducing peaks and valleys. Most of the energy delivered from charging stations occurred during daytime, which can be offset by installing PV panels.

The USC EV team concluded that it's possible to use EV chargers to balance load curve shapes based on the results from residential EV and associated charging stations. There was a small amount of energy used in the daytime while large amounts were used in the evening which makes the 24 hour charging energy distribution curve desirable to the utility company.

Based on the charging station usage from the ride share program and associated charging stations, the USC EV team found that EV chargers can be used to adjust the level of the load curve shapes by reducing peaks and valleys.

UCLA EV team demonstrated that the implemented system was able to effectively monitor charging behaviors, such as voltage, current, power consumption, total energy consumption, and time and duration of each charging session. Results showed that the DCFC had the most optimal charging efficiency and could serve the emergent charging events rapidly while the level 1 charging infrastructures were more suitable for users who charged regularly and longer. The data collected could be used for charging behavior estimation to achieve charging optimization.

The detailed case study for the Level 1 and Level 2 chargers were successfully conducted by UCLA EV team to show the system's real-time monitoring feasibility and all of the charging data were successfully reported to control center. The collected data could be further analyzed for charging optimization according to different charging demands.

10.2.7 Car sharing programs: Distribution Effects of Car / Ride Share Program

This demonstration studied charging habits of EV users based on type, time of connection, duration, consumption and utilization. Models were created to study the impacts of large scale deployment of EV chargers based on the economic analysis conducted on customer profiles.

The following are three types of EV users that were studied:

- Large corporate LADWP users
- Large corporate UCLA users
- Typical owners of EVs in the residential areas within LADWP service territory

Methodology

This demonstration was completed in conjunction with studies on monitoring of Chargers, Power Usage, and Car Usage demonstration with the same assumptions and methodology where LADWP purchased more than fifty EVs to be utilized in the fleet for the Car/Ride Share Center (used for daily activities by personnel) to demonstrate the distribution effects of the EV Car/Ride Share program, and the various Smart Charging demonstrations. To accommodate for the new EV's charging standards, the existing EV charging infrastructure was retrofitted. The program included addition to parking spaces, signage, and EVs to the existing LADWP fleet.

USC team studied the charging patterns of EV usage by large corporate fleets that have charging patterns similar to typical gas stations, typical owners of EVs in the city and suburbs, and typical EVs employed at a car rental, which was changed to typical EV's that are employed at a university since the availability of EVs within the car rentals was very limited.

Data was collected from charging stations, FleetCarma, LADWP survey, dispatch table, and electrical meters within LADWP service territory. The demonstration was separated into 3 tasks as shown below:

A. Car Usage, Charging Station Usage and Power Usage of large corporate fleet users:
   1) 36 assigned EV users
   2) 30 ride share users
B. Charging Station Usage and Power usage for each individual user in UCLA
C. Charging Meters Information and Power Usage of typical owners in LADWP local residential area from 2/1/2016 to 4/30/2016.

For more details on the execution of each task, refer to Appendix X.

Technologies Deployed

The following were deployed for this demonstration:

- AMI Meters
- More than 1000 EV Chargers
- FleetCarma
- More than 60 Electric Vehicles

Success Criteria

Description of success criteria and status for this demonstration on Car Usage, Charging Station Usage and Power Usage of 30 ride share users are listed below:

1) Raw data and overall analysis (completed)
2) Individual EV user's habit analysis from June 2014 to July 2015 (completed)
3) Comparison of all EV Users from June 2014 to July 2015 (completed)

Description of success criteria and status for this demonstration on Car Usage, Charging Station Usage and Power Usage of 36 assigned EV users are listed below:

1) Overview of all EV usage and charging (completed)
2) Overview of LADWP assigned EVs and carpool EVs (completed)
3) Individual EV user habit analysis (completed)
4) Comparison of EV and non-EV (completed)
5) Comparison of all EV users (completed)

Description of success criteria and status for this demonstration on Charging Station Usage and Power usage for each individual user in UCLA are listed below:

1) Individual EV user habit analysis from 07/2014 - 08/2015 (completed)
2) Comparison of EV users in UCLA (completed)

Description of success criteria and status for this demonstration on Charging Meters Information and Power Usage of typical owners in LADWP local residential area are listed below:

1) Individual typical owner analysis from 2/1/2016 – 4/30/2016 (completed)
2) Comparison of typical owners (completed)

Observations

USC evaluated the customer's charging habit from one year of survey data of LADWP employees driving EV from June 2014 to July 2015, EV usage data in FleetCarma from May 2015 to May 2016, LADWP's dispatcher's data from May 2015 to May 2016, charging records of EVs at UCLA from July 2014 to August 2015, and LADWP residential EV rebate meter data from February 2016 to April 2016.

In the evaluation of LADWP EV user habits, the analysis was from June 2014 – July 2015. Since FleetCarma was installed in June 2015, there were few car records. The records showed EVs were not used for after-work activities as EVs were only used by LADWP during working hours.

For the period of May 2015 – May 2016, 36 EVs were assigned of which 22 of them were PHEV and 14 were BEV. LADWP EV user analysis showed the average PHEV user consumed 7510KWh which was 2774KWh higher than the average BEV user. The reason may be that BEV users worry about their EV's battery capacity, and so, they did not use their vehicles for long distance trips and did not use them until the battery was fully charged. PHEV users would fully drain the battery in their vehicles for long distance trips and in many trips; therefore, PHEV users used more energy and had longer mileages.

The time range for the assigned EVs used for Carpool, most of the trips occurred during 7 AM to 3 PM since the cars were owned by LADWP and carpool users returned them before leaving. Since all carpool cars were mainly used for work purpose, there were no peaks in long distance (70% of trips were within 5 miles).

229 EV users were recorded at UCLA from July 2014 to August 2015 for the habit analysis. Top 10 heavy energy users were studied for their plug-in start time and durations and statistic results of individual users were used for insights to make city planning and future installations of EV charging infrastructures by utility companies.

In the study of typical EV owner habits analysis, record showed the total amount of charged energy for 10 users was higher than 1300 kWh. By applying the average value of 3.5 miles per kWh, the USC EV team concluded all the users drove at least 4000 miles in three months in their EV. On average, EV users charged their EV more than once a day.

For more details on the demonstration, refer to Appendix X.

Results

USC EV team found differences in carpool users between assigned car users, but the assigned car and carpool Battery Electric Vehicles (BEVs) had similar distribution charts and had the same energy consumption habits. BEVs car users kept their EVs above 50% SOC.

UCLA records of EV users showed that the charging amount per day was different among EV types from energy distribution. USC EV team found the plug in time could be long for EV users who had a small capacity battery and would charge daily for small increments of energy.

2% of 223 residential users in the typical EV owner habit analysis charged for than 100 times in 3 months. Frequent charging habits may have been resulted from worry about low power or long charging duration at home.

10.2.8 Grid Impact: Various Loading Scenarios

This demonstration was designed to evaluate EV loading on the distribution grid by looking at eight different loading scenarios that were modeled and analyzed. The requirements included the evaluation of interaction of EVs, application of battery storage, and charging and discharging processes.

Methodology

The demonstration on Generation, Transmission, and Distribution Effects of EVs was related to this demonstration on EVs effects of Various Loading Scenarios in the study of Grid Impact. USC modeled systems to assess impacts based on the collected data using LADWP infrastructure from various substations, distribution automation equipment, and AMI meters throughout LADWP's service territory. The assumptions for this demonstration were outlined in section 10.2.7 Car sharing programs: Distribution Effects of Car / Ride Share Program. Details on the objectives of each loading scenarios can be found in Appendix Y.

The demonstration used more than 1 year of data collected from use case 2 (reading power consumption for vehicle connected to chargers), use case 7 (use of batteries in grid (G2V and V2G), and use case 17 (integration of EV and solar). Circuit models were built to reflect different circuit scenarios as follows:

1) Underground vs. Overhead
2) Industrial vs. Residential
3) Pad-Mounted vs. Overhead Transformers
4) Voltage Control (regulators / capacitors)
5) Renewables (solar / battery)

Charging station usage data by time series were reviewed to create load models categorized by level 2 or 3 chargers and analyzed with different loading models. The demonstration took into consideration of the type of system performance for analysis, required type and level of system modeling, and the representation on size of the system used. A small system of network model was used and power flow implications of the various loading scenarios were assessed. The details activities taken can be found in Appendix Y.

System demonstration using actual system data was not performed due to the lack of available metered data. There was a lack of tools and capability to represent the vast LADWP infrastructure at Chatsworth in electromagnetic transient analysis model, lack of the metering infrastructure to cover a sufficient amount of the LADWP system, and there was extensive delay in the implementation of the data collection of system.

Technologies Deployed

AMI meters, 10 EV chargers, DA/SA equipment, MDM, and EVs were planned for deployment in the Chatsworth area for this demonstration; however, none of these were fully deployed due to the lack of available metered data.

Success Criteria

Description of success criteria and status for this demonstration to meet the general system modeling and representation requirements are listed below:

1. Select a network model to enable analysis of EV distribution effects as described in the SGRDP Preliminary Design Document (completed)
2. Select software programs for the development of the model (completed)
3. Attach multiple EV charger loads of various classifications to the EDD and PSCAD models and the IEEE 34 system (completed)
4. Reveal the aggregate effect of multiple EV charger loads at substation connections to the transmission grid using the EDD and PSCAD models and the IEEE 34 system representations (completed)
5. Test various loading scenarios using EDD and PSCAD models (completed)
6. Using PSCAD harmonic analyses are setup on the test systems with the goal of revealing when the IEEE 34 system will encounter the most severe harmonics when multiple EV loads as well as renewable energy are connected (completed)

The demonstration on the system using actual system data was not performed. Equipment deployment for system demonstration was reduced caused by the reduction in the anticipated EV penetration in Chatsworth.

Observations & Results

Based on the PSCAD simulation studies, it showed less damage could be caused to the grid and battery when customers charge EV battery with higher SOC. Results of the study suggested locations of EV charging station should be chosen far distance away from transformer as they act as a harmonic source, EV charging stations located around industrial area should be equipped with protective systems and have limits on number of EVs to ensure high power quality.

Underground cables are more prone to EV harmonic impacts than overhead transmission lines. Overhead distribution lines are able to withstand more electric vehicles to be charged compared to underground cables.

The requirements from the design document were not realistic to construct LADWP infrastructure network for the system analysis to develop electromagnetic transient analysis modeling of any significant size of the LADWP system.

10.2.9 Control of Chargers

This use case was designed to demonstration the Control Center's ability to automatically manage the on/off state of chargers based on various scenarios collected from the system, charger, and electric vehicles.

Methodology

The WINSmartEV infrastructure was used for this demonstration where the Super Control Center sent signals to the UCLA's EV chargers with pre-defined algorithms for level 1 and 2 EV chargers to control their on/off state based on various conditions from the sensor data and user profile.

Direct communication was used with the chargers if they were equipped with onboard communications and control; otherwise, control was handled through a smart meter's remote switching capability. A heuristic rule engine was used to determine when to charge or backfill the vehicle's battery automatically. The rules were based on transformer capacity, peak demand, time of use rate, critical peak pricing, user preferences on charging and backfill, battery profile, battery temperature, fault signal from BMS, and SOC.

Initially, UCLA EV team planned to develop and demonstrate algorithms for Level 1 and Level 2 EV chargers, demonstrate ability to manually control chargers, monitor and evaluate data from event, document and report on the control of chargers. Through UCLA research and experiment effort, UCLA SMERC's level 2 EV chargers were allowed for the change of charging current on the charging stations.

The final methodology used is illustrated in the Success Criteria.

Technologies Deployed

In order to complete this demonstration, the following systems/equipment were deployed:

- Super Control Center
- EV Control Center
- 137 EV Chargers
- Electric Vehicles

Success Criteria

The success criterial have been successfully completed as listed below.

1) Vehicle operator plug in the vehicle when arrived at the charging station
2) Vehicle operator use mobile application to activate a charging station
3) Control Center records initial Charging Record (starting status)
4) Control Center sends commands to Charging Station to activate the charger
5) Charging Station charges EV with appropriate current based on charging scheduling algorithm
6) On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
7) Control Center detects very little current are being drawn by the EV

8) Control Center records final Charging Record (ending status)
9) Control Center sends commands to end the charging session
10) Control Center informs vehicle operator results of charging session
11) Control Center resets the Charging Station for new charging session

Observations & Results

Observations showed the control center and mobile could remotely control level 1 and level 2 charging stations with charging algorithms. Charging time equality was ensured with the round-robin algorithm (equally assign charging time to different EV connected by calculating time ratio) when more than 1 EV was connected to charger. In the first come first serve scenario, equal-sharing algorithm allowed EVs to get charged as soon as possible and improved user satisfaction.

Several issues were discovered in the demonstration; for example, offline issues for EVSE gateways for level 1 and level 2 boxes and Tesla controlling issues.

Results of the demonstration showed that instantaneous EV chargers would be more ideal since the Super Control Center and charging algorithms would have more data to improve determination on the control of EV chargers. Fifteen to twenty minute reads were used to produce more data for instantaneous reads.

Power allocation was found to be unstable for the existing charging sessions as new EVs were plugged in and initiated charging sessions due to dynamical modification of energy sharing schedule and charging power for different charging outs required by the round-robin algorithm for level 1 and equal-sharing algorithm for level 2 outlets.

There were several areas of concern from the demonstration; one was the misunderstanding of users on the round-robin algorithm, where users switched charging sessions automatically. Another area of concern was with the communication network where some meters went offline due to the communication issues and when that happens, the EVSEs affective cannot be controlled and the schedule algorithm cannot be performed as normal.

The UCLA EV team collected data from October 2015 to February 2016 and can be referred to Appendix AB.

The planned impact and benefit was to use the ability to control chargers to allow a utility to perform load shedding if and when necessary. However, the planned impacts/benefits were not realized despite the Use Case being completed as UCLA did not implement the ability to control chargers that were charging and no load shedding events were performed at UCLA to utilize this technology.

10.2.10 Disconnect Charging EV

This use case was designed to demonstrate the act of disconnecting an EV from charging. Commands for disconnect or connect were initiated from the central control center or mobile application from the user to a specific charging station.

Methodology

The UCLA EV team used the Super Control Center under their WINSmart EV infrastructure to demonstrate 4 scenarios: to disconnect a fully charged EV, users disconnects the EV before it is fully charged, EV manually gets disconnected by the EV Control Center, and the EV get manually gets disconnected by a user through the mobile web application.

Direct communication was used with the chargers if they were equipped with onboard communications and control; otherwise, control was handled through a smart meter's remote switching capability. The charging stations were connected to local gateway. The local gateway received commands and compiled them into new commands that were dispatched to the designated charging stations.

The planned methodology and actual used methodology have been outlined below. The modification on the design of the demonstration was caused by the updates in the hardware designs by UCLA:

Planned Methodology	Final Used Methodology
1. Charging Station records EV Vitals	1. Vehicle operator plug in the vehicle when arrived at the charging station
2. Charging Station records Scenario Data	2. Vehicle operator use mobile application to activate a charging station
3. EV Vitals & Scenario Data sent to Control Center	3. Control Center records initial Charging Record (starting status)
4. Control Center sends commands to Charging Station	4. Control Center sends commands to Charging Station to activate the charger
5. Charging Station charges EV per commands	5. Charging Station charges EV with appropriate current based on charging scheduling algorithm
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data	6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
7. EV informs Station charging is complete	7. Control Center detects very little current are being drawn by the EV
8. Charging Station reports results of charge to Control Center	8. Control Center records final Charging Record (ending status)
9. Charging Station inform operator results of charging session	9. Control Center sends commands to end the charging session
10. EV Operator removes & stores Charging Cable	10. Control Center informs vehicle operator results of charging session
11. Charging Station resets for new charging session	11. Control Center resets the Charging Station for new charging session

Table 68: UCLA EV Team's Planned vs. Final Used Methodology - Disconnect Charging EV

Technologies Deployed

The Super Control Center, EV Control Center, Mobile Web Application, EV chargers, and EVs were deployed in order to complete this demonstration.

Success Criteria

The success criteria for this demonstration were to successfully execute the activities, which were achieved. The activities outlined above for the actual methodology used were accomplished.

Observations & Results

Observations showed that most EV users did not prefer to close their charging sessions through mobile application or web-applications. The EV users who did used their mobile application to discharge were not normal charging sessions as they were discharged with the energy consumption being close to zero, which indicated that the users may have changed charging location or re-submitted their charging sessions due to EVSE hardware issues. The charging power of level 2 chargers is faster than level 1 chargers. The closing charging and unplug behaviors indicated the user preferences over controlling their vehicles. For more observations and results along with data collection summary, refer to Appendix AC.

The planned impacts/benefits were to utilizing the ability to control chargers automatically or manually, so a utility would have the ability perform load-shedding if or when necessary. However, the planned impacts/benefits were not realized despite the Use Case being completed as UCLA did not implement the ability to disconnect vehicles that were charging and no load shedding events were performed at UCLA to utilize this technology.

10.2.11 Smart Charging through Mobile Interface

This use case was designed to display the status of EV chargers and to show if the EV chargers are charging.

Methodology

The same assumptions were used for this use case as the control and disconnect of EV chargers. In addition, an iOS application and an Android application were developed to enable users to manage their charging sessions, display real-time availability and location of EV chargers, receive messages/alerts regarding battery status and backfill.

The UCLA EV team demonstrated the following scenarios:

1) Level I Price-bid algorithm
2) Level II Price-bid algorithm
3) Historical Data for Price-based charging algorithm
4) User Price Preferences
5) Priority Charging

The Service Gateway software system was used to provide an open architecture and web-based interface which allowed integration with multiple protocol and platforms and provided open API and interfaces for mobile applications developers to create customized applications.

The main activities for this demonstration were to search for charging station, monitor charging process, and set up charging preferences. Those activities were to be accomplished by following this planned approach.

The planned methodology and actual used methodology have been outlined below. The modification on the design of the demonstration was due to the Vehicle-2-Grid (V2G) operations not being feasible for the regular EV users, so V2G operations were performed in the Control Center instead of the user's mobile device:

Planned Methodology	Final Used Methodology
1. Search for Charging Station	1. Search for Charging Station
a. User selects **Search** Option from Mobile App.	a. User selects "**Map of Available Stations**" Option from Mobile App or web interface.
b. Search defaults to user's location or allows user to select new location	b. Allows user to select location from participating locations
c. Map shows available Charging Stations based on selected location	c. Map shows available Charging Stations based on selected location
d. User selects desired Charging Station	d. User selects desired Charging Station
e. Map displays driving directions to selected Charging Station	e. Map displays driving directions to selected Charging Station
2. Monitor Charging Progress	2. Monitor Charging Progress
a. User selects **Alert** Option from Mobile App	a. User selects "Map of Available Stations" Option from Mobile App or web interface.
b. User enters Charging Station ID	b. Allows user to select location from participating locations
i. EV must be connected to Charging Station	c. Map shows available Charging Stations based on selected location
c. User preferences are displayed for verification (and changes)	d. User selects desired Charging Station
d. Monitoring process begins (based on preferences)	e. Map displays driving directions to selected Charging Station
e. Monitoring process stops when charging session is terminated or user logs out of system	
3. Set up Charging Preferences	3. Set up Charging Preferences
a. User selects **Preference** Option from Mobile App	a. User specifies preference when he/she starts a charging session from Mobile App.
b. User views and updates stored user preferences	b. User views and updates stored user preferences

c. User saves changes (or cancel to exit without saving)	c. User start the charging session with specified preference.

Table 69: Planned vs. Used Methodology - Smart Charging through Mobile Interface

Technologies Deployed

The Super Control Center, EV Control Center, Mobile Web Application, EV chargers, and EVs were deployed in order to complete this demonstration.

Success Criteria

The success criteria for this demonstration were to successfully execute the activities outlined in Methodology, which were achieved.

Observations & Results

Observations showed that variations of price preferences among users towards energy prices existed, price selection and the urgency of charging schedules were related, and different strategies could result in different values of energy consumption and costs. Features offered by the mobile application provided additional conveniences for users to find available EVSE. Scheduling algorithms from the requests and preferences optimized the energy consumption and reduced the energy cost for participating users.

Users were able to avoid high price time interval by shifting the energy demand lower-price regions. With such finding, direct relations between energy consumption values and energy prices were still required to derive the most optimal solutions. Prices under the pricing paradigm on the relationship between energy demand and energy prices could be used in the optimization program to minimize the total energy cost by shifting energy consumptions to lower price regions from high price regions. Additional observations and results can be referred to Appendix AD.

10.2.12 Various Vehicle Charging

This demonstration was responsible for observing and comparing charging performance on different EV makes and models. Purchased or leased vehicles were used in this research where tests were performed with the design and development of the open architecture EV chargers.

Methodology

The UCLA EV team purchased a Nissan Leaf, Chevy Volt, Ford Focus, and a Mitsubishi MiEV and leased a Tesla Model S. UCLA collected data from the mentioned EVs and EV chargers which charged various EVs throughout the UCLA campus. The UCLA EV team utilized the WINSmartEV infrastructure and completed the demonstration at the SG Power Lab, the various demonstration sites, and the SG EV Control Center. LADWP and USC also participated in the demonstration.

The planned demonstration steps are outlined below.

1) Charging Station records EV Vitals
2) Charging Station records Scenario Data

3) EV Vitals & Scenario Data sent to Control Center
4) Control Center sends commands to Charging Station
5) Charging Station charges EV per commands
6) On a periodic basis, Charging Station will report to Control Center status and accumulative charging data
7) EV informs Station charging is complete
8) Charging Station reports results of charge to Control Center
9) Charging Station inform operator results of charging session
10) EV Operator removes & stores Charging Cable
11) Charging Station resets for new charging session

This use case's design was similar to UCLA use case 3 (control of chargers), where EV charging sessions and power consumption were recorded by the EV control center; therefore, UCLA updated the final used methodology to use collected data to conduct analysis in terms of various EV make and Models' power consumption, report J1772 (North American standard for electrical connector for EV) communication issues with various vehicle, and report energy efficiency and other observations based on the operation of grant vehicles.

To accommodate different requirements for charging preference amongst drivers with different vehicle makes, commune distances, work habits, and hours, UCLA EV project team assigned the purchased and leased vehicles to researches and staff within the UCLA EV project team to replicate the various EV charging needs and preferences to test the scheduling algorithms. The assigned drivers also used the mobile application developed in this research.

Technologies Deployed

This demonstration utilized the deployed Super Control Center, EV Control Center, 137 EV chargers, and various EVs.

Success Criteria

The UCLA EV team completed the success criteria as outlined below for their use case's activities:

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. EV Vitals & Scenario Data sent to Control Center
4. Control Center sends commands to Charging Station
5. Charging Station charges EV per commands
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data
7. EV informs Station charging is complete
8. Charging Station reports results of charge to Control Center
9. Charging Station inform operator results of charging session
10. EV Operator removes & stores Charging Cable

11. Charging Station resets for new charging session

Observations & Results

The UCLA EV team saw the impacts on voltage drop on the ability to send power to the vehicle. Some of the examples are listed below:

- The Chevy Volt illustrated a high sensitivity-to-voltage fluctuation on the ability to get a charge.
- The Ford Focus showed an inability to re-start a stopped charging session after the charging cable was disconnected.

The final deliverable report from UCLA includes the findings and experiments conducted. Due to the variations in charging behavior found on the experimented EVs, UCLA modified the nature of the architecture of UCLA's system to improve the overall architecture by making it more robust and reliable with the multiple EVs. The UCLA EV team also reached out to various EV manufacturers to discuss findings and potential solutions to standardize the communications between the EVs, charging stations, and smart grid through technological solutions and/or standards modifications.

The Nissan Leaf was used for smart charging on level 1-3 chargers, research in battery SOC monitoring, and battery connection for applicability for V2G operation. Circumstance indicated that it was not possible to perform V2G demonstration on this make and model at this time due to the lack of warranty, vendor support, limited time, and concern of safety.

The Chevy Volt was used for smart charging demonstration with level 1 and 2 chargers. Due to a recent vehicle software update from the EV manufacturer, the SOC information was encrypted and cannot be retrieved at this time by the UCLA EV team. Its alarm system was activated when the EVSE lost power; this issue was resolved by adjusting the setting inside the vehicle. The Chevy Volt was not used for the V2G demonstration because it only had an AC onboard single-direction charger. Circumstance indicated that it was not possible to perform V2G demonstration on this make and model at this time due to the lack of warranty, vendor support, limited time, and concern of safety.

The Ford Focus was used for smart charging demonstration with level 1 and 2 chargers. It was unable to re-start charging session after it gets disconnected. It did not start charging if the charging session power was not provided within 5 minutes after the EV was plugged in. The Ford Focus could not perform V2G demonstration because it only had an AC onboard single-direction charger and also due to safety, warranty, lack of vendor support, and limited time.

The Mitsubishi-MiEV was used to demonstrate power back-feeding, smart charging on level 1-3 chargers, and design of renewable integration. It was compatible with three level of charging because it was equipped with J1172 standard and CHAdeMO protocol. A V2X box was developed to provide V2G function; it was used to within the AC 100 V power from the EV and then the AC power was converted into 48 V DC, connected through a grid-tie inverter to conduct V2G operation.

The Fiat 500e model was used to demonstrate charge using full power source. Observation showed if the duty cycle of the pilot signal was small (indicating low charging current was available), the initialization

charging process failed. With the initial duty cycle being high and later adjusted to low, the Fiat EV generated an error message “Service Vehicle Electrical System” and “Service Your Charging Station.”

Based on the collected observations and data, Nissan Leaf had the most compatibility with J1772 pilot signal communication schema; however, its battery had the most degradation rate among the studied EVs. Refer to Appendix AG for more information.

10.2.13 Grid Balancing and Management

This use case was designed to demonstrate the ability to monitor and control loads to help manage grid instability.

Methodology

The use case was based on UCLA EV team using their WINSmartEV infrastructure to demonstrate the ability to monitor and control loads to help manage grid instability by using non-critical loads (EV chargers and battery energy storage systems) to shed and smooth demand by sending demand response signals through the Super Control Center. A local distribution network with EV charging stations were used in the demonstration performed in the SG Power Lab, where the charging station load was switched on/off based on loading scenarios.

The activities executed for the demonstration are outlined below:

1) Charging Station records EV Vitals
2) Charging Station records Scenario Data
3) EV Vitals & Scenario Data sent to Control Center
4) Control Center sends commands to Charging Station
5) Charging Station charges EV per commands
6) On a periodic basis, Charging Station will report to Control Center status and accumulative charging data
7) EV informs Station charging is complete
8) Charging Station reports results of charge to Control Center
9) Charging Station inform operator results of charging session
10) Operator removes & stores Charging Cable
11) Charging Station resets for new charging session

Technologies Deployed

This demonstration utilized the deployed Super Control Center, EV Control Center, Battery Energy Storage System, 137 EV chargers, and various EVs.

Success Criteria

The success criteria for this demonstration were to successfully execute the activities outlined in Methodology, which were achieved.

Observations & Results

The UCLA EV team illustrated a system structure (designed to be compliant with the OpenADR standard) that was able to implement DR signals based on the maximum load predefined within each UCLA parking structure. The scalability with Virtual Devices was tested and the reliability of the Control Center was evaluated.

Observations pointed out that a middleware was required to aggregate and control a group of device for the Super Control Center (upper-level EMS system), could successfully implement the commanding role for energy management. For the load shedding result initiated from the Super Control Center, the Smart EV charging stations may be able to respond to a turn off command in less than a minute, verses reaching out to each individual EV charger, which may take approximately 3 minutes. Results showed that frequent change on charging current on an EV charging station could cause malfunction on the EV charger and will require a manual re-start of the EV charger. Refer to Appendix AH for additional details, such as data collection summary.

10.2.14 Community Storage of EV Batteries and External Storage

This use case was designed to demonstrate the use of EV batteries and battery external storage on the grid in the following scenarios:

- Battery Energy Storage System (BESS) used to regulate the voltage
- BESS used to smooth solar
- BESS used to cut the EV Charging peak demand
- Normal operation

Methodology

The UCLA EV team used their WINSmartEV infrastructure, as well as developed and installed a 62 kWh capacity battery storage system to complete the demonstration at the SG Power Lab, Various Demo Sites, and the SG EV Control Center. Detailed on-demand charger information which indicated the status of the charger and a regular transmittal of the charging duration was collected by having the EV charger communicated directly with the SG EV Control Center through an application interface, which was provided by the charger vendors and additional metering devices.

The EV project team installed charging stations for level 1-3 charging from various vendors in parking structures at UCLA and LADWP. Since most of the communication protocols on charging stations were proprietary, the UCLA EV team designed and developed an open-architecture charging station which allowed data collection on the detailed user data and circuit control to fully control the charging operations from the SG EV Control Center.

The planned methodology and actual used methodology have been outlined below. The original demonstration design was expanded after the UCLA EV team determined that the battery energy storage could be used to improve the EV charging load, power quality, and PV smoothing:

Planned Methodology	Final Used Methodology
A. Grid used to charge CES	A. BESS is used to regulate the voltage
1. CES receives signal from Control Center to charge	1. Local control frequently send the signal to check the availability of BESS
2. CES records CES vitals	2. Local control frequently send the signal to check the availability of GTI
3. CES vitals sent to Control Center	3. BESS and GTI send back the ready status signal
4. On periodic basis, CES will report to Control Center status and accumulative charging data	4. BESS records BESS vitals
5. CES informs Control Center charging is complete	5. BESS vitals sent to Local Controller
6. CES reports results of charge to Control Center	6. On periodic basis, BESS will report its status to local controller and accumulative data
B. CES used to charge EV	7. Measurement unit send periodically the voltage information of the grid to local controller
1. Charging Station records EV Vitals	8. Local controller send the reactive power control signal to GTI
2. Charging Station records Scenario Data	9. GTI operates in leading or lagging mode
3. EV Vitals & Scenario Data sent to Control Center	10. Local controller stores all the data
4. CES records CES vitals	B. BESS is used to smooth the solar
5. CES vitals sent to Control Center	1. Local control frequently send the signal to check the availability of BESS
6. Control Center sends commands to Charging Station (to charge) & CES (to discharge)	2. Local control frequently send the signal to check the availability of GTI
7. On periodic basis, CES will report to Control Center status and accumulative discharging data	3. BESS and GTI send back the ready status signal
8. On periodic basis, EV will report to Control Center status and accumulative charging data	4. BESS records BESS vitals
9. CES informs Control Center SOC is at minimum value or EV informs Control Center charging is complete	5. BESS vitals sent to Local Controller
10. CES reports results of discharge to Control Center	6. On periodic basis, BESS will report its status to local controller and accumulative data
11. EV reports results of charge to Control Center	7. Control center send periodically the power information of solar to local controller

8. Local controller calculate and generate the appropriate reaction signal
9. Local controller send the active power control signal to GTI
10. GTI operates charging or discharging mode
11. Local controller stores all the data
C. BESS is used to cut the EV charging peak demand
1. Local control frequently send the signal to check the availability of BESS
2. Local control frequently send the signal to check the availability of GTI
3. BESS and GTI send back the ready status signal
4. BESS records BESS vitals
5. BESS vitals sent to Local Controller
6. On periodic basis, BESS will report its status to local controller and accumulative data
7. Control center send periodically the DCFC power information to local controller
8. Local controller calculate and generate the appropriate reaction signal
9. Local controller send the active power control signal to GTI
10. GTI operates in charging or discharging mode
11. Local controller stores all the data
D. Normal operation
1. Local control frequently send the signal to check the availability of BESS
2. Local control frequently send the signal to check the availability of GTI
3. BESS and GTI send back the ready status signal
4. BESS records BESS vitals
5. BESS vitals sent to Local Controller
6. On periodic basis, BESS will report its status to local controller and accumulative data
7. Local Control periodically check the status of battery module includes voltage, temperature, SOC, SOH, and charging and discharging current limits, etc.

8. Local controller calculate and generate the appropriate reaction signal
9. Local controller send the active power control signal to GTI
10. GTI operates in charging or discharging mode
11. Local controller stores all the data

Table 70: Planned vs. Used Methodology - Community Storage of EV Batteries and External Storage

Technologies Deployed

The following systems/equipment were used to complete the demonstration:

- Super Control Center
- EV Control Center
- PV Array
- Battery Energy Storage System
- 136 EV Chargers
- Electric Vehicles

Success Criteria

The success criteria for this demonstration were to successfully execute the activities outlined in Final Used Methodology, which were achieved.

Observations & Results

To improve the voltage regulation, the Battery Energy Storage System (BESS) was employed. Voltage variation due to uncontrollable nature of PVs and EVs could have a direct impact on the operation, such as load tap changers, voltage-controlled capacitors banks, and line voltage regulators, all of which might cause additional step-voltage changes. Based on the delays in the control of the existing devices, observations showed that minute-based step-voltage variation might be experienced.

The demonstration showed that more frequent operation of these devices led to more requirements for maintenance which shorten the expected life cycle of these devices. The compared results from active and reactive power control with reactive power control showed the distribution system controlling the active power was important for voltage regulation.

In a different scenario where the application of the BESS for solar smoothing was studied, observations found as PV penetration increased beyond a certain threshold, the fluctuations of the PV power would negatively impact the operation of power system. Such finding suggests it would be unreliable to have a power system that solely depends on multiple renewable energy sources. For instance, during fast fluctuations, the power system operators had limited response capacity thus if the fluctuation exceed the permitted level, there was a risk of a complete power system failure. Such risk was significant in a weak distribution gird with a high PV penetration rates, such as islands. An experiment was performed to

determine the best outcome of this scenario where a new filtering approach and prediction technique was developed to improve solar fluctuation. The approach of using the root-mean-square deviation or root-mean-square error criterion reduced the solar fluctuation by 86%.

In the third scenario, the BESS was utilized to reduce the peak demand of DCFC. The experiment demonstrated the best practice through using the battery storage system to distribute the DCFC demand over the time and cut the grid power demand.

The normal operation of battery storage system during charging and discharging was demonstrated as the last scenario. It observed the variation of cell temperature, showing the SOC and DC voltage.

Results showed that the BESS, Direct Current Fast Charge (DCFC), solar, and AC meter were reporting their status with high frequency. Date, time, DC voltage, DC current, Inverter active and reactive power, DC power, SOC, SOH, max and min cell temperature, and max and min cell Voltages, along with other parameters were reported every 2 seconds from BESS. Generation and consumption power were reported every minute from solar and DCFC. Every 2 seconds, the AC grid voltage was captured. Data collection summary is available in Appendix AI.

10.2.15 Inductive Charging

This use case was designed to demonstrate the use of inductive coupling between the charging station and EV.

Methodology

The assumptions for the demonstration were for LADWP to procure an inductive charger and an inductive charging EV. Once the inductive charger is installed, a meter will be used to collect data. A driver was to be assigned to drive the EV to simulate the usage for the LADWP EV team to gather charging data using FleetCarma. The UCLA EV team were to research the theory behind inductive charging.

The selected EVs were to be retrofitted with adaptors and circuits in order to support inductive charging. Inductive charging stations were to be purchased and installed in selected areas to monitor power consumption and usage patterns and collect additional information to evaluate safety issues, convenience of usage, charging efficiency, effect of improper aligned coil, and temperature change on the coils.

An electromagnetic field (EMF) is used in inductive charging to transfer energy between two inductive coupling coils with one coil attached to the charger and the other coil attached to the EV's battery. Inductive charging has a lower risk of electrical shock compared to conductive charging since no direct contact with cables is required by the EV operator, which is essential in an uncovered parking area under wet weather conditions.

Disadvantages of inductive charging include:

- Lower efficiency
- Increased resistive heating in comparison to conductive charging
- Require additional adaptors and circuits need to be added to the EV which increases the weight of the EV

The demonstration steps are outlined below:

1) Charging Station records EV Vitals
2) Charging Station records Scenario Data
3) Charging Station records Inductive Charging Data
4) EV Vitals, Scenario, & Inductive Charging Data sent to Control Center
5) Control Center sends commands to Charging Station
6) Charging Station charges EV per commands
7) On a periodic basis, Charging Station will report to Control Center status and accumulative inductive charging station data
8) EV informs Station charging is complete
9) Charging Station reports results of charge to Control Center
10) Charging Station inform operator results of charging session
11) Charging Station resets for new charging session

The demonstration steps were modified since the UCLA EV team was not able to procure an inductive charger and an inductive charging capable EV. Thereby, the UCLA EV team could not send commands to control the inductive charger. Instead, the LADWP EV team procured and installed an inductive charger and inductive charging capable EV and was able to collect data for this use case.

Technologies Deployed

AMI meter, EvaTran inductive charger, FleetCarma, and a modified Nissan Leaf were deployed to complete the demonstration.

Success Criteria

The success criteria and status are outlined below.

1) Charging Station records EV Vitals – Complete
2) Charging Station records Scenario Data – Complete
3) Charging Station records Inductive Charging Data – Complete
4) EV Vitals, Scenario, & Inductive Charging Data sent to Control Center – Complete
5) Control Center sends commands to Charging Station – Not Done
6) Charging Station charges EV per commands – Not Done
7) On a periodic basis, Charging Station will report to Control Center status and accumulative inductive charging station data – Complete
8) EV informs Station charging is complete – Not Done
9) Charging Station reports results of charge to Control Center – Complete
10) Charging Station inform operator results of charging session – Not Done
11) Charging Station resets for new charging session – Not Done

Steps 5, 6, 8, 9, and 10 were not completed because the charger was unable to communicate with our systems.

Observations & Results

AMI data from the charger, EV trip and charge data were collected. Data collection summary can be referred to Appendix AP. Results of demonstration showed that charging efficiency may be a concern when coils are aligned properly. Most EV drivers may feel safer to operate inductive charging during a snowy or rainy weather since plug-in cables are not required. Its relative high cost in installation compared to conductive EV chargers may be consider as some infrastructural modifications may be required to fit the charging station.

10.2.16 Generation, Transmission, and Distribution Effects

LADWP's Integrated Resource Planning group supported the USC EV team to analyze electric vehicles' effect on generation, transmission, and distribution for the present and future. Economic benefits of renewables on the grid with EV were also analyzed by the USC EV team.

Methodology

The USC EV team received information on the 2014 Load Forecast from the LADWP Integrated Resource Planning group to demonstration production simulation case studies in order to assess the cost and emission impact of various EV load profiles and study methodologies. The USC EV team used information resulting from other use cases to research the EVs' effects on the generation, transmission, and distribution system under low, medium, and heavy EV charging load scenarios. The study was based on the discrete calendar years (8,760 hours) which included investigation of reductions in equipment loading and circuit losses, economic benefits of load balancing and peak-shaving/load-levelling.

The use of solar energy to supply power to the EV chargers and grid was also analyzed by the USC EV team with the assumption the solar energy would be used in the daytime to supply energy to the grid or charge EV's or Community Energy Storage centers. Power quality and system reliability issues associated with renewable energy resources and distribution grid coupled with large-scale deployment of EV chargers were evaluated. The demonstration steps are outlined below:

1) Run Use Case 14 (Gage of the Future) and 16 (Aggregation of the Batteries) for more than 1 year to collect enough data to analyze and report results
2) Review Charging Station usage data and EV usage data by time series
3) Review any anomalies and report

The demonstration steps were modified due to the time constraints, the USC EV team could not complete two out of the four study cases. Due to permit issues and time constraints, a wind turbine was not deployed, thus none of the demonstrations related to the wind turbine was completed. Photovoltaics were used for the use case on renewables effect on generation, transmission, and distribution.

The demonstration steps were modified (as final methodology) as shown below:

1) Run Use Cases 8 (Distribution Effects of Battery Aggregation and Backfill), 11 (Distribution Effects of EV's on the Grid), 14 (Garage of the Future), 16 (Aggregation of the Batteries), 18 (Monitoring of

Charger, Power Usage, and Car Usage), and 19 (Distribution Effects of Car / Ride Share Program) for more than 1 year to collect enough data to analyze and report results

2) Review Charging Station usage data and EV usage data by time series
3) Review any anomalies and report

Technologies Deployed

AMI meters, EV chargers, FleetCarma, EVs, and solar panels were deployed to complete the demonstration.

Success Criteria

The success criteria for this demonstration were to successfully execute the activities for final methodology, which were achieved.

Observations & Results

The economic dispatch study was not conducted as designed in the original plan to test residential, corporate, and rideshare PV load profiles for actual system data. Therefore, the results of the demonstration did not illustrate benefits in meeting the objectives in assessing the effects of EV charging load manipulation has on the generation, transmission, and distribution systems. Results did not show a difference in impact as with any other load demand increases. The results were not based on PV charging load profile.

Power flow analysis showed there was no thermal overload for normal, single and credible double contingency conditions during adverse off-peak conditions. Findings also include pre-existing high voltages conditions were generally reduced by EV charging. No violations were shown from post-transient voltage stability and transient stability analysis of critical contingencies. Data collection summary and additional finding are referenced in Appendix AQ.

10.3 Problems Encountered

Risk_Title	Risk Description	Likelihood of Occurrence	Cost Schedule Impact	Risk Consequence	Risk_Mitigation
Stakeholder	ECC and Power Quality groups to provide permission of installation of wireless SCADA nodes in the DS88. Currently wireless SCADA nodes are not the normal practice at LADWP, so	Medium	Medium	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Cost or schedule	Work with the ECC and power quality groups to get permissions. ECC provided approval.

	we are not sure if permission will be granted.			overruns	
Stakeholder	Fast DC level III charger installation is behind the schedule due to lack of materials and facility owner permission.	low	low	• Failure of a team to meet one or more team objectives, with no material trickle-up impact to the program • Minor schedule or cost overruns, with no material trickle-up impact to the program	Escalate to the proper authority to obtain permission. Permission was provided.
Technical	No access to AMI data	High	High	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Cost or schedule overruns	Work with the responsible parties to clear constraints and bottlenecks. Help facilitate the process. Raise concern level and escalate as needed. Provide resources and establish firm timelines for delivery and closely monitor and track to completion. Project re-baseline in progress
Staffing	No dedicated labor resources to implement web interface for DA or EV chargers.	Medium	Medium	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns	Contracted resource to perform the work.

Stakeholder	AGM approval for JFB garage of the future not obtained which postpones permitting and construction. Project currently at a standstill.	High	High	• Failure of a team to meet one or more team objectives, with no material trickle-up impact to the program • Minor schedule or cost overruns, with no material trickle-up impact to the program	Approval was granted.
Technical	Communication Distribution Automation (DA) Service Provider Equipment Communication. The mechanical switch is connected to live feed. Completion of tasks is dependent upon turning off the 34.5kV feeder line. The switch is not designed for live on/off testing. (It will destroy the switch).	High	Low	May be unavailable to ECC, who is requesting commissioning for usage	Determined that EV team does not have to commission the switch by start of operation. Schedule to have the switch controller removed from the pole to remove radio and test the system.
Staffing	PI interface for storage of OH transformer monitor data is delayed due to staffing shortage	Medium	Medium	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Cost or schedule overruns	Work with the responsible parties to clear constraints and bottlenecks. Raise concern level and escalate as needed. Provide resources and establish firm timelines for delivery and closely monitor and track to completion. Project re-baseline in progress
Stakeholder	Data not being provided for EV DWP Usage on loaned out cars	Low	Low	Failure to complete Car Ride Share report	Fleet Carma completed in EV Control Center - DRMS which allows data collection.

Technical	Functionality limitations of the AMI meters may impact research	High	Med	Critical impact, does effect scope of use cases	Data output defined, all data can be derived. Found alternate ways to find the required data and utilized UCLA's demonstrations to cover the limitations of our meters.
Technical	EV team may not be able to test 34.5 KV switch due to DWP safety standards	Medium	Low	Delay of switch testing will delay the commissioning of equipment and ECC interface	PM to identify DWP safety/ compliance standards for this work. EV team will request assistance when working on 34.5 switch.
Technical	EV team may be unable to access UCLA smart charger data due to access issues around the UCLA private information agreement related to the access program	Med	High	EV team will be unable to check status of smart charger, study application design and function, review requirements	Legal team is reviewed access contract to determine whether or not access will be granted to EV team. EV team has been granted access to Smart Charger data
Technical	Distribution Automation capacitors are currently non-functioning due to radio communication limitations.	Low	Low	This will delay schedule of Chatsworth deployment.	EV team is to pursue cellular communication solution, currently testing, ordering, and configuring equipment. EV team to meet with CS regarding security/network design for RTAC communication.
Technical	Sunverge's energy management system in the GOF may be unable to provide certain data points (Battery Use Cases)	Med	Med	EV team may be unable to collect all data points for battery charging data.	Sunverge working on implementing the changes to their API. Completed EVCC integration w/ UCLA WML Control Center. Integrated Sunverge dashboard into control center.
Technical	Data from DTM (Distribution Transformer Monitoring) may be unable to be transferred into Pi Historian	Med	Med	DR team will not have transformer data for key analysis Other DWP groups also are interested in acquiring DTM data	DWP team has access to data via web services. Currently evaluating additional year costs. EV team will evaluate other options for data collection going forward.

Schedule	EV team may not get all the data points they need from ECC and the voltage regulator (DS-88)	High	High		ECC has agreed to make adjustments the voltage regulator manually to allow DR to perform their use case.
Schedule	Retrieval of EV application dates for AMI meter installation to pull up dates may cause delays in project	Low	Low	Schedule delays	EV to discuss potential support w/ PEPMO. Work is about 20% complete, should be complete by EOM
Schedule	Construction crews are poorly instructed on scope of work needed for L3 chargers and are not receiving CWPs (Design for installation) to finish the construction within project timeframe	Med	Low	Schedule delays	EV having ongoing meetings with construction crew to facilitate continued progress.
Schedule	UCLA L1 Charger outlet is not functioning, ongoing issues may impact data collection	Low	Low		EV team is tracking to see if issues is resolved by UCLA
Schedule	The cap bank controller socket needs to be replaced for cap bank 088-22-sc5 to install the new cap bank control.	Low	Low	Schedule delays	EV team requested replacement, cap banks have been installed.
Schedule	Level 3 charger at UCLA is not accessible to the public	High	High	UCLA cannot perform their use case for EV-Battery integration studies.	UCLA have proposed plans to allow the public to use the chargers free of charge. Plans were modified and accepted by both parties.
Schedule	Level 3 charger at USC is not accessible to the public	High	High	USC cannot perform their use case EV Studies.	USC relocated chargers.
Technical	EV team may be unable to access GOF charger data	Med	Med	Will limit extent of data collection for GOF Demonstrations	Mitigated by using a critical load port

Technical	AMI/EV Smart Meters for EV chargers at city hall are unable to communicate due to insufficient cellular communication network.	High	Low	Inability to collect consumption data from EV Chargers installed in and around City Hall.	AMI team installed cellular meters at city hall, 4 will not communicated, 5 will communicate.
Schedule	EV team may not be able to execute remote connect/disconnect function	High	High	EV use cases and demonstrations become severely limited	Used UCLA's data for the demonstration of the control of chargers
Technical	Sunverge's API power monitoring may not be implemented	High	Med	Data may not be available	Did not implement. Ran use cases semi manually
Technical / Schedule	EV meter integration may not be in line with CC&B	High	High	Delay of EV meter deployment will delay data collection	Work request for installation of rebate EV meters for chargers have been completed. Completed installation at Main St. and JFB EV meters installation for public locations, close at this time since new non-billing SP type cannot be tested at this time.
Personnel	Lack of Resources may delay the demonstrations and use cases for the project	High	High	Unavailable resources to work on project, delaying progress (EV programmers) 5/7/15	Contracted resources.
Schedule	Certification is still pending for turbine and grid interactive inverter	High	High	Timeline is not certain	Decision was made not to install, unable to find a certified source on damaged blades.
Cost	Future FCI battery might fail prematurely	High	Med	Product produced in Germany so lead time of 6 wks.	Replaced FCI battery. Currently in process of purchasing of emergency battery to be used for powering the mechanical transmission logs in the RTU in event of power outage.
Schedule	Lack of tools and access for on-site	High	Med	Impacting productivity	Resolved by granting access and tools.

	programming resource				
Schedule	Lack of info. 34.5kv line. Need to confirm if our scaling factors are valid	High	Med	Would delay schedule while waiting for confirmation	Completed hardware upgrade.
Technical	SGRDP servers/system went down 8/11/15- no work can be done	High	High	delay project schedule	Patched OS servers. Four servers moved to new environment. Clean-up completed
Technical	UCLA reported an overheating issue on their EV chargers at the UCLA campus	High	Med	Causing widespread disconnections of chargers. They are not able to complete charging session. Cause is known due to hot weather.	Solution was implemented now running additional tests.

Table 71: Problems Encountered in EV Demonstrations

10.4 Lessons Learned

The major lessons learned for EV includes:

- DTM monitor functionality can be replicated by AMI meters
- Remote cap controllers are helpful for detecting failed cap cans/ cap switches
- Insufficient certification of hardware can cause significant delays to the project
- Discontinuous and insufficient staffing can cause significant delays to the project
- EDD program: There were great difficulties to learn and use the program due to the fact that the program is still is in its infancy and there is a lack of documentation and user base. Training by the software developer to LADWP and USC personnel was conducted initially to provide the necessary support. Furthermore, EDD was hired to help in the development of the model as well.
- Observation based on the simulation studies is only possible at the present time. Equipment deployment, and about one-years of data collection will be required to conduct the actual system demonstrations.
- Helpful to have a commercially available collection system like FleetCarma. However, having good documentation and vendor support would streamline the data process for direct analysis since the output of data from FleetCarma was lacking certain information.
- The design document requirement to construct LADWP infrastructure network for the system analysis for use case 21 (various loading scenarios) was not realistic. It was beyond the scope of the demonstration work to develop electromagnetic transient analysis modeling of any significant size of the LADWP system.

- A reduced set of various loading scenarios were done with EDD program, since harmonic analysis was not possible with this model
- Studies using a smaller system representation of the IEEE34 bus system were sufficient to assess the impact of the loading scenarios.
- In the study of controlling chargers, including disconnects of chargers, the lack of communication between the BMS and the server side algorithm makes it difficult to reduce the delay of disconnecting operations. In addition, certain meters may go offline due to the issues of communication network. Thus, the EVSEs affected will be out of control and the schedule algorithm cannot perform normally
- In the study for smart charging through mobile interface, additional research will need to be focused on the optimization of pricing strategies and the energy management algorithms. More survey on user preferences on energy price, charging control strategies, and mobile application interfaces should be conducted to better understand users' energy consumption behaviors.
- For future 2-way charging, it should include acquisition of the EV SOC (critical for monitoring and control purposes and for optimization of charging/discharging sequence); develop protocol-regardless interface that would allow V2G of different vehicles with different charging ports; scale up feedback power on one EV and to study multiple EV with V2G capability.
- State of Charge (SOC) information was difficult to obtain, the J1772 standard did not provide that information.
- Tesla model S had multiple integration issues causing the need to reevaluate pricing and scheduling algorithms
- An intermediate agent is required to aggregate an control a group of device for the upper-level EMS system to implement the commanding role in energy management
- A Super Control Center (middleware) could initiate a turn off command to the Smart EV charging stations to obtain a response in less than a minute while the initiation made to an individual EV charger may take 3 minutes to process the command.
- A Manual restart of the EV charger will be needed when an EV charging station gets a frequent change of charging current. In addition, the EV charging station may result in malfunction on the EV charger.
- The best practice to control EMS is to manage a macroscopic view at the PS level while enabling the EV control Center its own operation ability for microscopic adjustment over each charging station.
- Fluctuations of PV power would negatively impact the operation of power system. Such risk was more pertinent in a weak distribution grid with high PV penetration rates (i.e. islands).
- Problems may occur in the aggregation of batteries if the communication network is not proficient as the infrastructure requires a reliable communication network.
- Equipment used in the integration of EV and Solar will need its own interface for an upper-level EMS system.
- Solar unit (SIS) unit was not capable of remotely avoiding PV energy usage or Grid connection. To overcome this limitation, the DWP EV team used a manual disconnection of grid connectivity and

PV connectivity to force the SIS unit to follow the schedule of charging/discharging the EV based on a predefined scenario.

- The solar unit was not capable of disconnecting the grid remotely nor capable of stopping the load feed. It always fed the load from available resources acting like an uninterruptible power supply (UPS). Future plans and operations with the usage of SIS should be considered.
- EV Internal measurements were not readily available for research purpose.
- Due to the inductive charger's location and the charger's elevated profile, the inductive charging pad was damaged by a DWP service truck, thus it may be an impractical technology to implement due to the location (external - get damaged) (internal - too expensive to install).
- Time constraints and permitting issues prevented the procurement and installation of a wind turbine for the demonstration. As such, wind renewable data was unavailable for use case #20 (Generation, Transmission, and Distribution Effects).

10.5 Conclusion

Based on the completed demonstrations on renewables and battery integration, we found Smart charging (G2V) for the purpose of "valley-filling" and V2G are very effective charging options compared to others. The key point of these strategies are managing peak load condition with EVs discharging to the grid to save electricity usage and shave the peak of the load curve. Reactive power will increase dramatically after the Battery Storage and EVs are plugged in, which will cause problems related to voltage stability in power grid. Battery storage will generate higher harmonics when compared to no battery storage in the system which may damage the system and devices. Such observations and findings from the demonstration can help utilities plan technologies deployment and solutions and reduce system costs.

Studies on the distribution effects showed the microgrid will add reliability and security to the campus electrical demand. An optimization process was implemented to find the most optimal microgrid plan using the best available energy resources. The most optimal option was determined be a combination of microturbines, PVS, batteries, inverters, and the main grid (LADWP).

In using a ride share program to obtain charging station usage, the USC EV team concluded that it is possible to use EV chargers to levelize load profiles by removing or reducing peaks and valleys and it would be advantageous if utility companies applied V2G technology to direct the EV customers to start charging in the middle of night to increase the off-peak demand and help optimize the actual daily load curve. Charging stations delivered most of the energy to all EVs during daytime, which could be offset by installing PV panels.

Observations from the EV demonstrations determined that users are able to avoid high price time interval by shifting the energy demand lower-price regions. The pricing paradigm between energy demand and prices can be used to optimize customer programs to reduce the total energy cost by shifting energy consumptions from high price regions to lower price regions.

By demonstrating the monitor of charging behaviors, the EV team was able to identify the most optimal charging efficiency that could serve the emergent charging events. In addition, features offered by the mobile application provided additional conveniences for users to find available EVSE.

The planned impact and benefit of using EV batteries to provide a utility with the ability to reduce peak demand, prevent blackouts/brownouts, which can reduce cost was achieved by the UCLA EV team who were able to shed approximately 28 kW during a load shedding event. Scheduling algorithms from the requests and preferences optimized the energy consumption and reduced the energy cost for participating users.

Below is a list of prominent benefits to power and EV industry which were resulted from EV demonstrations:

- Unique current throttling feature of the created charger enables flexible power management schema to increase power quality and grid stability.
- Multiplexing features and scheduling algorithms maximized and optimized usage of existing power circuits.
- WINSmart EV platform allows rapid integration of various components (V2G, BESS, PV, and DCFC) for power management.
- Issues and lessons learned identified along with data collected provide valuable reference for future large scale EV technology deployment.
- Provide guidance for future system development at LADWP and other utilities on distribution system reliability, asset management, infrastructure optimization, and cost effectiveness.

11 Cyber Security Overview

11.1 Summary

Within the Smart Grid Regional Demonstration Program, the Cyber Security project is responsible for addressing security issues in meeting concerns of LADWP and its customers by designing and developing cybernetic system architecture that is secure, scalable and practical. Due to changing customer environment characterized by home-area networks (HANs), co-generation capabilities, plug-in electric vehicles, smart appliances and smart Heating, Ventilating and Air Conditioning (HVAC) systems, grid applications require an open-access approach to development, which highlights the significance of effectively addressing the issues of security. The purpose of the CS project is to design a secure smart grid that is scalable, practical and resilient to attacks and failures despite the malicious or inadvertent intentions.

To support these needs, the SG requires the timely exchange of information between the utility operators and its customers. Those exchanges will necessarily use both private and commercial computer networks which raise additional serious security issues. The CS project within the SGRDP is responsible for addressing such issues and creating the security strategy for the entire SGRDP system.

The recognition that new approaches are required to address such risks is also resonant with the Department of Energy's "Smart Grid Cyber Mission". To achieve needed security, the CS project adopts a defense-in-depth strategy that integrates two complementary design approaches. The first approach draws upon standard or 'classic' security techniques, such as role-based authentication, authorization and application design guidelines, which provide needed security features, while preserving usability. The second approach will develop 'next generation' CS techniques, tailored to the SG, that improve its resilience to attacks and faults. The CS project also implemented a risk assessment process, patterned on federal guidelines FIPS 199 and NIST SP 800-30, and a rigorous test and validation process to comply with testing requirements described in DE-FOA 0000036.

The generated list of threats is used as input for a variety of tasks, namely: (a) overall risk analysis and mitigation (Risk Assessment Section) (b) attack analysis for understanding the flow of threats through the system from an attacker's perspective, (c) fault analysis for understanding threats from a system failure perspective (Fault/Failure Tree Analysis Section), (d) as inputs for the design of the detection, diagnosis and response component and (d) as inputs to generation of test cases for the CS design.

The CS component is driven by a number of requirements in the nominal system definition, and has its own decomposition of requirements from the top level. After a thorough assessment of these requirements, the CS project team has identified multiple areas where CS services can be provided to the SG project's core functionalities (AMI, DR, CB, and EV). These operations broadly fall under the following categories:

- Routine Operations
- Security Event Response– Detection, Diagnosis, Response (DDR)
- Maintenance– Risk Assessment and Security Updates

During routine operations, features like encryption, authentication, and access control will be tightly integrated with the normal operation of the SG. At the same time, detection services will monitor the system for unusual events that may signal a cyber-attack, and if a security event is detected, security functions will respond to maintain system security. In some cases, these responses will be automated, and in others, guided by the operator.

CS operations span the whole entire system and include:

- Day-to-day operation of CS components under nominal conditions
- Updates and routine maintenance of CS components, to ensure all knowledge bases are up-to-date, and that all components continue to operate within reasonable constraints.
- Real-time behavior of automated monitoring and response functions when detecting and responding to an incident.
- Operator responses to detected incidents, and interactions with CS components to secure the system and maintain critical grid functions.
- Forensics, updates, and maintenance of CS components after anomaly operations have completed, intended to correct the consequences of an incident and resume full system operation in a timely manner.
- CS support for business continuity operations.

11.2 Deployment Architecture

The SGRDP's computer security components reside in many components of the architecture. Security servers referred to as security infrastructure support policy and identity management, intrusion detection, and situational awareness located in a physically secured location, central to the SGRDP IT Operations of LADWP. Firewalls and application proxies are located at the boundaries of protection domains and interact with the policy servers over the network.

Software developed is included in the mission oriented components of the SGRDP architecture and was deployed in locations dictated by the mission requirements and designs of the other project teams. These software and server components call functions to make security decisions, and to implement security functionality. These modules were developed by the security team and are components of the security architecture, but are deployed as part of the mission oriented components of the SGRDP on computers in locations remote from the servers that constitute the security infrastructure of the SGRDP.

11.3 Demonstrations Key Steps

Table below lists the CS demonstrations and their key steps for completion:

SOPO/Final Reports	Functions To Be Demonstrated	Use Case/Scenario	Key Steps
• **Grid resilience against cyber attacks**	1. Demonstrate the capability to detect attacks. 2. Demonstrate the capability to diagnose the provenance of attacks. 3. Demonstrate the capability to remediate or contain the consequences of cyber-attacks.	DDR-Cyber Physical-AMI	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		DDR-Cyber Physical-DR	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case

		DDR-Data Theft-DR	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		DDR-Energy Theft-AMI	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case

		DDR-SG Assets-AMI-CGR	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		DDR-SG Assets-AMI-HE	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case

		DDR-SG Assets-CB Portal	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		DDR-SG Assets-DR-DRAS	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case

		DDR-SG Assets-DR-DRDR	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		DDR-SG Functions-AMI-BILL	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case

		DDR-SG Functions-AMI-OM	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		DDR-SG Functions-DR-LR	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
• **System Integrity**	1. Demonstrate the detection of manual inserted changes to software on all classes of nodes. 2. Demonstrate the reconfiguration and/or recovery to legitimate software configuration on affected components.	DR-CS-1	Required system knowledge for design of scenario Knowledge of data schemas/interfaces DDR Detector - Design and Implementation

		DR-CS-4	Required system knowledge for design of scenario Knowledge of data schemas/interfaces DDR Detector - Design and Implementation
		EV-CS-1	Dependent on AMI/DR system going operational
		EV-CS-2	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
• **Secure Data Management**	1. Demonstrate the detection of modified billing, configuration and audit data, and behavior of system upon detection. 2. Demonstrate the denial of attempts to access or transmit data where such access or transmission is counter to defined information flow policies.	EV-CS-3	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case

		EV-CS-4	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		CB-CS-1	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		CB-CS-2	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case

•Testing: Effectiveness (The design of the security mechanisms for the Smart Grid demonstration project – this is a prerequisite to the deployed system, and to this demonstration/The model/architecture of the cybersecurity infrastructure for the Smart Grid.)	1. Demonstrate the systemic response to various threats such as malware penetration and physical threats that will affect parts of the Smart Grid.	CO-CS-1	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		CO-CS-2	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case
		NOM-CS-1	1. Containment Architecture 2. Construct CS Monitor/Control 3. Basic DDR: 4. SIEM 5. Network IDS/IPS 6. Gather Project Information 7. Develop Use Case

		Subsystem Testing	test bed
		System Testing	test bed
•**Testing: Predictive capability (The architecture of the cyber security infrastructure for the Smart Grid demonstration project – this is a prerequisite to the deployed system, and to this demonstration/ The model/architecture of the cybersecurity infrastructure for the Smart Grid.)**	1. Demonstrate the issues (limitations and possibilities) facing a full-scale deployment of the cyber-security approach.	Operational Readiness Testing	test bed/ all use cases listed above
		Evaluations for Risk Assessment	test bed
		Regression Testing/Maintenance	all use cases listed above

Table 72: CS' demonstrations' key steps

11.4 Technologies Deployed

The deployed systems were the Cyber Security (CS) Detection, Diagnosis, and Remediation (DDR) system, the Security Information and Event Management (SIEM) system, data monitors, AMI Data Collection Engine (DCE) Interface Software, simulated data injectors, DDR alert emitters, and alerts.

This demonstration requires the underlying infrastructure supporting the CS environment and basic DDR. The basis of DDR functionality is exercised in different scenarios as described below:

DDR capabilities for AMI

- Collect customer consumption data.
- Store sufficient history of consumption data for each customer to calculate statistics.
- Process consumption data through one or more detection algorithms.
- Write records of detections of anomalies to a permanent store for downstream processing by operators or diagnosis algorithms.
- Display detected anomalies and provide status monitoring for CS components on a visual dashboard

DDR capabilities for DR, EV, LADWP Intrusion Protection System (IPS)

The capabilities are listed below:

- DR - Collect records of DR application events and related data from DR log files through an agent installed on the DR machine.
- EV - Collect records of EV events from EV logs through an agent installed on the EV machine.
- IPS - Collect records of network intrusions and anomalies detected by LADWP's commercial IPS.

- Store collected records in an operational DDR database.

Basic DDR has six component types:

1. Collector – A software component (interface from a data source into the CS component). Implemented collectors were AMI DCE Collector (software dependencies: Apache Tomcat 7.0.42 or higher; Apache Axis 2 1.6.2 or higher; JDK 1.7.0_45 or higher), AMI CG-NMS Collector (software dependencies: Apache Tomcat 7.0.42 or higher; Apache Axis 2 1.6.2 or higher; JDK 1.7.0_45 or higher), Intrusion Prevention Systems (IPS) Collector (software dependencies: Syslog-ng 3.4.2 or higher; Python 2.6-2.7.x; PyMongo 2.6.3 or higher; a 2014 release of pytz or higher; supervisord 3.0 or higher), and Demand Response Automation Server (DRAS) System Log Collector (software dependencies: Snare Enterprise Agent for Windows 4.2.5 or higher; Syslog-ng 3.4.2 or higher; Python 2.6-2.7.x; PyMongo 2.6.3 or higher; a 2014 release of pytz or higher; supervisord 3.0 or higher)
2. Database – Central database where all data and events flow. It is implemented using MongoDB (software dependencies: MongoDB version 2.6.3 with no special configurations or packages) database management software.
3. Detector Bank – Container for the set of detection algorithms. It provides functionality to manage the execution of detection algorithms. Software dependencies include: Flask 0.10.1, Jinja2 2.7.3, MarkupSafe 0.23, Werkzeug 0.9.6, backports.ssl-match-hostname 3.4.0.2, gevent 1.0.1, greenlet 0.4.2, itsdangerous 0.24, matplotlib 1.3.1, nose 1.3.3, numpy 1.8.1, pymongo 2.7.1, pyparsing 2.0.2, python-dateutil 2.2, pytz 2014.4, six 1.7.2, tornado 3.2.2, wsgiref 0.1.2.
4. Detector – An algorithm applied to a single data stream to detect anomalous behaviors.
5. Diagnosis – An algorithm that correlates information from various streams of data to identify relevant events.
6. Visualization – Display CS component state.

LADWP implemented Security Information and Event Management (SIEM) for visualization and monitoring of DDR events for mass meter disconnect, Denial of Service (DoS) attacks against smart meter communication infrastructure, potential energy theft, infrastructure system change detection and diagnosis, DDR firewall alert actions.

The SIEM implemented at LADWP also consists of visualization and monitoring of smart grid infrastructure health and security events on smart meter communication infrastructure alerts and events, smart meter alerts and events, smart meter key management system alerts and health check events, and smart grid zone firewall alerts.

Data monitors interface to various data sources and obtain security-relevant data which gets stored in the DDR database.

AMI Data Collection Engine interface software subscribes to the Data Collection Engine for meter data and writes to the data to the DDR database.

The simulated data injector was used to generate simulated meter data to statistically enlarge data sets to evaluate defensive capabilities in attack scenarios as it would not be feasible to deploy failure to operational systems.

DDR alert emitters retrieve events of interest from the DDR database and transmit the events to LADWP SIEM system for visualization for operator to review and act.

DDR Security Alerts are based on current business processes used as baseline within the LADWP environment where the DDR detectors and diagnostician banks write events to the DDR database with the DDR emitters monitoring and forwarding alert events to the SIEM.

11.5 Demonstrations

11.5.1 Grid Resilience Against Cyber Attacks

This is a demonstration of the Grid's active defenses against cyber-attacks. It takes into account the accuracy and timeliness of detection and response and the outcome will lay out the pros and cons that accompany the full-scale deployment of such an active cyber defense.

The required components were Data Protection Intrusion Detection, Policy, Identify and Key Management.

Methodology

For this demonstration, LADWP deployed various containment technologies, including a front end firewall mediating access from the internet to all DWP assets, the deployment of a virtual local area network (VLAN) containment between zones within the DWP network infrastructure and SmartGrid zones, a Cyber Security (CS) Firewall, and data-power appliances which served as an application layer firewall capable to enforcing policies on the flow of information between the corporate zone, demand response infrastructure, and AMI zones in the SGRDP deployment. Deployment of the containment technologies was guided through smart grid specific architectural development including the definition of protection domains guided by the functional and authorized information flows necessary to meet the policy requirements for confidentiality, privacy, integrity and resilience for the smart grid.

The demonstration required implementing Detection, Diagnosis, and Remediation (DDR) infrastructure which detects and diagnoses cyber security-related events by analyzing the collected data and sends events to the SIEM systems for logging, display, and operator action. The LADWP Smart Grid SIEM system will receive security-related data DDR and other data sources, stores that data in its databases, and provides monitoring, visualizing, and reporting capabilities on those data.

Success Criteria

The success criteria for Grid Resilience against Cyber Attacks include the successful completion of all use cases. Additionally, periodic reports documenting the results of this demonstration along with a final report will be generated as a part of the success criteria for the demonstration area.

The success criteria for the DDR component are to implement these capabilities:

- Maintain a capability for timely detection and response
- Mitigate the consequence of cyber event
- Correct exploited vulnerabilities
- Restore affected systems, networks and equipment

11.5.2 System Integrity

This demonstration area was responsible for the detection of manual inserted changes to software on all classes of nodes, the reconfiguration and/or recovery to legitimate software configuration on affected components, and the protection of audit and configuration data. This demonstrated the ability of the Smart Grid to detect and recover from compromises of system integrity, including software and firmware modifications (possibly resulting from malware attacks), and the addition of unauthorized physical components to the system.

Methodology

The CS Project team implemented numerous security technologies in order to maintain system integrity. These include end-to-end encryption, virtual private networks, asymmetric cryptography, key management, identity management, access control, policy management, firewalls, privacy enforcement, audit record generation, intrusion detection/prevention system, and firmware download integrity checks.

Success Criteria

The success criteria for System Integrity include the successful completion of all use cases and deliver period reports documenting the results of this demonstration along with a final report.

11.5.3 Secure Data Management

This demonstration area was responsible for the detection of modified billing, configuration and audit data, and behavior of the system upon detection and the denial of attempts to access or transmit data where such access or transmission is counter to defined information flow policies. This demonstration shows the ability of the Smart Grid infrastructure to limit the flow of customer, configuration, and audit data according to defined policies and to protect the integrity of the data.

Methodology

To demonstrate the use cases and meet the success criteria for this demonstration area, the CS Project team implemented security services to different parts of the Smart Grid in order to manage secure data.

Success Criteria

The success criteria for Secure Data Management include the successful completion of all use cases. Additionally, periodic reports documenting the results of this demonstration along with a final report as a part of the success criteria for the demonstration area.

11.5.4 Testing Effectiveness of Security Measures Within the Smart Grid Architecture

This demonstration area was responsible for the systemic response to various threats such as malware penetration and physical threats that will affect parts of the Smart Grid. This demonstrates through emulation on the Defense Technology Experimental Research (DETER) cyber-security test bed, the effectiveness of the security measures within the Smart Grid architecture.

Methodology

To demonstrate the use cases and meet the success criteria for this demonstration area, the CS Project team ran a series of simulated attacks on a cyber model of the Smart Grid control and data transmission plane. This model was implemented on a DETER test bed at USC, where the CS team had complete control over the testing. This allowed the team to simulate cyber-attacks on the Smart Grid model and demonstrate the cyber response.

Success Criteria

The success criteria for Effectiveness Testing include the successful completion of all use cases. Periodic reports documenting the results of this demonstration along with a final report will also be generated as a part of the success criteria for the demonstration area. Additionally, the design of the security mechanisms for the Smart Grid demonstration project and the model/architecture of the cyber-security infrastructure for the Smart Grid will be provided as a part of the success criteria.

11.5.5 Testing: Predictive Capability When Extended to a Full-scale Grid Implementation

This demonstration area was responsible for the issues facing a full-scale deployment of the cyber-security approach. This demonstrated the effectiveness of the proposed security capabilities when extended to a full-scale implementation of the Grid.

Methodology

To demonstrate the use cases and meet the success criteria for this demonstration area, the CS Project team put the Smart Grid system through additional testing phases. First, the system was inserted into a high fidelity, fully operational domain, such as the microgrid. A selection of appropriate test runs were executed from the subsystem and system testing and additional testing were performed as required. During these tests, evaluations were performed in order to complete the risk assessment and evaluate the performance of the system at a high-level. Once the system is placed in an operational environment, a suite of smoke tests and core functionality tests will be performed as updates are delivered to the system.

Success Criteria

The success criteria for Predictive Capability Testing include the successful completion of all use cases. Periodic reports documenting the results of this demonstration along with a final report were generated as a part of the success criteria for the demonstration area. Additionally, the design of the security mechanisms for the Smart Grid demonstration project and the model/architecture of the cyber-security infrastructure for the Smart Grid were to be provided as a part of the success criteria.

11.6 Observations & Results

The CS Project team was able to complete all demonstrations pertaining to AMI. Basic DDR was not implemented for DR, EV, or CB. The CB environment was not set up in time to demonstrate DDR capabilities. The DR environment was configured late and logging capabilities was not available, therefore, the demonstration was not completed. The EV environment did not have a system with logging capabilities; therefore, the demonstration was not completed. Departure from planned methodology, observations, recommendations and lessons learned are detailed in the Cyber Security for Smart Grid: Final Progress Report which can be referred to in the appendix.

Below are some highlights from the demonstrated use cases:

Grid Resilience Against Cyber Attacks

Scenario: Meter Reading Services - DDR can monitor such events to detect unauthorized or unexpected meter changes by correlating them with other auxiliary information such as scheduled configuration changes, and technician work-orders.

Scenario: Operator monitors system security status - The SIEM consumes events from the DDR system, as well as classic security events, and displays them on two different SIEM dashboards. This provides near real time visual notification to operations staff that are monitoring the health and security of the smart grid environment.

Scenario: Detection of security events with no response - The SIEM consumes logs from the Intrusion Detection System (IDS)/ Intrusion Prevention System (IPS), CS Firewall, Data Power .etc and events from the DDR system; any failed components report alerts that are displayed on two different SIEM dashboards. This provides near real time visual notification to operations staff that are monitoring the health and security of the smart grid environment. If there is no operator response (X number of minutes) in a given threshold, the SIEM will send emails to the respective analyst based on the support calendar.

Scenario: Detection of security events with automated response - In our current design, the SIEM does not automatically make changes to systems in the operating environment. Only manual actions are taken whereby the operators monitoring the SIEM alerts drill down into specific details to investigate the many raw events that contribute and trigger the DDR alerts.

Scenario: Detection of security events with operator-in-the-loop response - In our current design, the SIEM does not proactively make changes to systems in the operating environment. Rather, operators monitoring the SIEM alerts drill down into specific details to investigate the many raw events that contribute and trigger the DDR alerts. Operators may also use this information to cross-reference with other systems, such as the Work Management System, to identify any false positive alerts due to operational activities (meter deployment, maintenance, planned outages, etc.).

Scenario: Failure of CS component - detection and response - The SIEM consumes logs from the IDS/IPS, CS Firewall, Data Power, etc and events from the DDR system, any failed components report alerts that are displayed on two different SIEM dashboards. This provides near real time visual notification to operations staff that are monitoring the health and security of the smart grid environment.

Secure Data Management

Scenario: Revenue Protection - DDR detects potential energy theft attempts, which can be manifested by tampering with the AMI meter, and recalibrating the usage reading using authorized vendor software. The recalibration essentially changes charging or reporting parameters causing low usage to be reported to the SIEM to display to the operator.

Scenario: Outage Detection - With the DDR capability the system was able to correctly detect and diagnose disruptions occurring between the smart meters and the utility and provide reports to the SIEM for alerts. Power Up and Power Down events might be indicative of power problems at the meter. DDR can also correlate a power up event with other auxiliary information such as customer status to infer situations where a non-bill-paying customer circumvented a power turn off by the utility.

Scenario: Meter Maintenance - With the DDR analysis capability the system was able to apply pattern matching to look for events which were being generated periodically, and we discovered a few meters which were generating the "Reverse rotation detected" event almost 20 times every day, for almost a year. We reported this finding to the AMI team, and on further investigation by field technicians, the meters were discovered to be faulty. Similarly, we discovered that looking for simple patterns such as "long sequences of zero readings" or "consecutive meter reporting failures" in AMI meter usage data can be used to infer problems such as "potential energy theft", or "meter communication failures" respectively.

Scenario: Meter Bypass Detection - DDR correlated the occurrence of "remote disconnect exceptions" from a large number of meters within a short span of time, and raised an alert. The generated alert was reported to the SIEM to display to the operator.

System Integrity

Scenario: Meter Removal Detection - Removal tampers, when seen along with other anomalies such as zero usage readings, missed readings, or other meter failures can be indicative of malicious activity, and are thus very relevant for DDR. DDR flags a stream of such events as a meter failure. Further, DDR correlates this event with other security events, and/or configuration change events to infer potential malicious activity. DDR outputs a Potential Energy Theft Attempt alert, with an anomaly description as "Zero usage detected and correlated with meter tamper events". The generated alert is sent to the SIEM for display to the operator.

Testing: Effectiveness

Scenario: Risk Assessment updates - The most important component in mitigating vulnerabilities and risks is performing a Risk Management & Assessment process throughout each stage of the AMI implementation project lifecycle. The threat landscape is consistently moving, new threats and vulnerabilities will occur. The risk assessment cycle is a vehicle that constitutes a disciplined and methodical approach to identifying and mitigating new threats. Since the Smart Grid includes systems from the IT, telecommunications, and electric sectors, the risk assessment process was applied to all three sectors as they interact in the Smart Grid. The SGRDP risk assessment was largely patterned on the National Institute of Standards and Technology Special Publication (NIST SP) 800-30 methodology, incorporating the Federal Information Processing Standard (FIPS) 200, "Minimum Security Requirements

for Federal Information and Information Systems", and FIPS 199, "Standards for Security Categorization of Federal Information and Information Systems" where the levels of impact are defined. In addition, the SGRDP risk assessment process assimilates the pertinent elements of the assessment process as described in the National Institute of Standards and Technology Interagency Report (NISTIR) 7628 Volume 2 that is specific to the Smart Grid.

Testing: Predictive capability

Scenario: Modification or implementation of monitor - During the deployment of the SGRDP, special focus was paid to system integrity. For the Advanced Metering Infrastructure (AMI) components of the system, requirements were imposed on the vendors to verify updates to software and configuration of meters through a digital signatures applied by the utility. With respect to other software components of the SGRDP, end systems are instrumented with an integrity monitor that utilizes Another File Integrity Checker (AFICK) tool to communicate the checksums of all new and changed software components to the detection, diagnosis, and remediation database within the security component of the SGRDP. Changes are authorized by consulting a policy database of allowed software components maintained within the DDR mechanisms, and any changes not authorized result in a diagnostic event that is generated and presented to operators through the (SIEM) system.

11.7 Problems Encountered

Risk Title	Risk Description	Likelihood of Occurrence	Cost Schedule Impact	Risk Consequence	Risk Mitigation
Staffing	Project manager is undefined, lack of progress updates and participation in re-baseline	Medium	Medium	• Failure of the program to meet one or more key objectives. • Exposure of LADWP to significant negative media coverage • Substantial cost or schedule overruns	Working with the CS team while a project manager is being defined. PM onboard.
Staffing	Data Power Integration Services with IBM has not been confirmed.	Low	Low	•Data flow cannot occur between SGRDP zones	Worked with IBM to resolve issue.

Technical	PenTest scope, schedule and permissions not clear. CS also needs to clarify the lifecycle that will be pen tested.	Med	Med	CS may not be able to identify and holes or gaps in the system, these can potentially be exploited or identified by external audit	CS is working on scoping pen testing via risk analysis. Vulnerability assessment has been completed; this will help determine pen testing scope. VA results are being analyzed and will be shared with impacted parties. Completed
Schedule	SIEM schedule may potentially slip	Low	Low-Medium	Delay project schedule.	Finalized schedule and completed implementation.
Schedule	Lack of systems integrator for project may affect the final integrated SGRDP demonstration	Med	High	Delay project schedule.	SI has been brought on (7/2014). They are currently evaluating state of SGRDP systems to identify work required to be done. This will determine overall scope/recommendations and project impact.
Technical	CS may be unable to monitor DR, EV, and CB systems due to issues with SNARE	Med	High	Impact scope/ demonstration	The CS team worked with DR to install the SNARE system. The SNARE installation completed for EV. SNARE for CB will be replaced by rSYSLOG when CB moves from Windows to Linux. Able to collect some data from DR and EV including more than 9 million log messages from the DRAS production machine, 600,000 from the DRAS test machine, and 460,000 from EV (see attached). However, the log messages from DR do not provide enough information to be used

	in the detection and diagnosis of DR application-related security events. JPL and the DR Team met and put a plan place to modify the DR logs to provide detailed application-level events, but it was not completed. The vast majority of the messages in the current DR logs at this time are common Windows events generated by the OS rather than by DR. Also the EV logs do not provide application level events to their server's Windows logs at this time.

Table 73: Problems Encountered in CS Demonstrations

11.8 Lessons Learned

11.4.1 Program-Level System Engineering

System engineering must be incorporated into the overall program. This is necessary to establish: a detailed, integrated architecture for the overall program's system of systems; a systematic allocation of requirements and functions; systematic cross-element technical trade studies; processes for the identification and resolution of system-level technical issues; inter-element interface engineering and documentation; system-level identification of, and planning for, inter-component dependencies; etc. The lack of any significant, sustained systems engineering effort resulted in a program that was implemented as set of isolated "stove-piped" projects. It also had other consequences, some of which are described in subsequent sections.

From a cyber security perspective, this meant that security issues were not adequately addressed early in the life cycle and in a systematic way across all program elements.

11.4.2 Program-Level System integration

System integration activities must be incorporated into the program early, and continue through program-level system testing. The lack of a program-level system integration function meant that the melding of individual systems developed by program elements into an integrated whole was problematic. There were no significant program-level integration resources, integration planning, or system-level integration or testing activities. In particular, it would have been helpful to identify early in the program a prioritized set

of cross-program operational scenarios (or use cases) to guide the design, integration, and testing of the overall system.

The lack of program-level system integration had many negative consequences for cyber security, including ongoing difficulties in obtaining the data needed from other program elements.

Cyber security is inherently a cross-cutting function, in that to provide security one needs something to secure. In the case of the SGRDP, the goal of the cyber security project is to secure the integrated, interoperable smart grid system - not just individual projects such as Demand Response (DR) or Electric Vehicles (EV). Systems have been implemented and program level system integration has taken place in areas that have been prepared for such a task. Unfortunately, the lack of all systems maturity holistically has reduced ability of LADWP to perform program-level system integration (requirements and design). Individual project focused on focused on designing and implementing their own systems (e.g., demand response for the DR system).

Due to cutting edge nature of this technology and the need to "design and build" some aspects, designs have changed and the definition of what to secure has changed as well. That has been the primary impact of not having an official system integrator. Essentially, the system integrator function has been mitigated by cross functional meetings where these similar issues are discussed.

The overlying issue is the readiness of systems that are outside of the SGRDP control and scope that delayed the possibility of a system integrator doing their job. The SGRDP dependency caused this design and build scenario which impacted the integration of a system.

11.4.3 Program-Level System Testbed

The lack of a program-wide integrated system testbed (containing all the required hardware and software for all program elements) meant that it was: difficult to identify inter-element technical issues early; not possible to integrate or test individual program elements in a realistic, integrated, test environment; not possible to exercise and evaluate off-nominal behaviors (attacks, faults) without harming the operational system; etc.

The lack of such a testbed was a particularly acute problem for cyber security, since it precluded deliberately introducing simulated attacks in a controlled, non-operational environment in order to evaluate detection, diagnosis, and remediation capabilities.

11.4.4 Modeling and Simulation

Our research work on simulation and analysis of attacks on the smart grid demonstrated the need for a multi-layered, integrated modeling approach to enable accurate evaluation of such complex, heterogeneous, system-of-systems. For instance, consider the case of a cyber-physical attack that originates in the cyber domain, and impacts the physical domain. An accurate analysis of such an attack would require a model of the cyber domain, a model of the physical domain, and more importantly a model of the cyber-physical interface that allows the attacks to propagate across the cyber-physical interface.

11.4.5 Planning for Operations

It is important to design and implement the project with an eye to operational deployment. This means that areas such as maintenance processes, exception handling, code documentation etc. should be clearly addressed to lay the groundwork for a smooth transition to operations at the end of the project. In retrospect, this topic received insufficient attention.

The operational scenarios (or use cases) mentioned above would also have contributed to a focus on operations.

11.4.6 Data Flow Tools and Processes

Given the complexity of, and operational restrictions within, the utility's environment, tools and processes that support the mapping of data flows through that environment – both during design and during integration and testing – are invaluable in assessing risk as well as in designing the defensive architecture. For example, identifying and understanding the nature of various intermediate nodes that data must flow through (e.g., data power devices, firewalls, DMZs, routers etc.) would enable the identification of possible interception points for a man-in-the-middle attack when assessing risk.

11.4.7 Data Management

It is important to pay attention to the architecture, processes and principles behind the storage and backup solutions for the handling large datasets. Specifically, here are some issues that should be clearly addressed: accessibility and access control; resource allocation; processing diverse, non-homogenous data; and requirement changes between the development and operational environments.

11.4.8 Avoidance of High-Risk Communications Protocols

The use of a full-duplex, bidirectional, always-on communication protocol (such as Web Sockets) as a communications mechanism should generally be avoided, or at least carefully evaluated, in this type of environment.

At one time such a protocol was considered for use by a program element. Our initial risk assessment of such mechanisms revealed several concerns, some of which are:

- *The "always on" nature of such protocols means that servers need to keep an open connection to millions of clients, which clearly poses scalability and security risks. For example, a massive DDoS attack can be launched against the utility servers from millions of clients sending arbitrary data on the open connections;*
- *Further, such protocols perform a one-time authentication of their clients while establishing the initial connection, and clients and servers are free to exchange any messages thereafter. This feature allows malware compromising the home-service gateways to easily hijack the authenticated session to send arbitrary data to the server (ex: spoof DR hacks), or intercept and manipulate the data coming from the server (ex: perform lower than requested load reduction).*

11.5 Conclusion

The LADWP approach to cyber security for smart grid includes a number of deployed and planned systems to meet the SGRDP. The focus of our analysis was on the following three deployed systems: the Cyber Security (CS) Detection, Diagnosis, and Remediation (DDR) system, the Security Information and Event Management (SIEM) system, and the deployment of a Network Containment and Isolation Strategy.

DDR Security Alerts:

The DDR system provides alerts based on current business processes and the established baseline within the LADWP environment. The DDR detector and diagnostician banks write events to the DDR database. The DDR emitters in turn monitor and forward alert events to the SIEM for the purposes of logging, visualization, and reporting.

The types of DDR events currently being consumed and visualized by the SIEM include: energy theft, denial of service, mass meter disconnects, system integrity events, and DDR firewall alerts. The DDR systems were able to provide an additional layer of security for the Smart Grid environment that requires more than the typical defense-in-depth security approach.

Classic Security Events:

The LADWP SIEM system deployed was designed to consume raw security events from classical security systems such as firewalls, VPNs, the smart grid public key infrastructure (PKI) system, smart grid communications systems, and application firewalls. SIEM logs from these data feeds were consumed and visualization was performed on the SIEM dashboard. Additionally, correlation rules were developed to match these raw events to LADWP's business processes and unique environment. The SIEM is also using these raw events to provide reliability and system stability information to management on a monthly basis.

Network Containment and Isolation Strategy:

Multiple deployed isolation mechanisms include the DataPower application firewall proxy which manages the flow of sensitive information out of the LADWP corporate zone, and from the AMI component to other SGRDP zones.

Existing LADWP firewalls and VLAN separation including the deployment of carefully defined fault containment regions.

An SGRDP Security Firewall which monitors flows between SGRDP domains and implements remediation for denial of service and other detected attacks

Cryptographic techniques for integrity and confidentiality applied through the communications protocols used for demand response, AMI, customer behavior, and security functions of the system.

System integrity capabilities to validate system changes before installation on hardware in the field, and to identify unauthorized system software and configuration changes to all elements in the SGRDP.

Extensive simulation, testing, and analysis of the system impacts w***ere*** done to understand and record the cyber and physical compromise that was demonstrated throughout the SGRDP implementation. Below are some limitations and possibilities to be understood when deploying large scale AMI environments.

The AMI system should provide an application programming interface (API) to retrieve CGR-meter associations. Detection and diagnosis of certain security threats requires us to correlate data from AMI meters and their corresponding CGRs. For example, to infer a Denial-of-Service attack on a CGR would require us to correlate communication failures from meters behind a CGR, and events from a corresponding CGR. This requires the detection and diagnosis processes to maintain a reliable model of CGR-AMI meter associations in the system.

Full Scale Deployment Issues:

It is important to address cyber security across all system elements from the outset of a program, and continue to do so throughout the systems development life cycle. While that was the stated intention and plan within this program, it occurred only to a limited extent. Many factors contributed to this; lack of program-wide system engineering, system integration, a systems integration architect, and a system testbed. Implementing comprehensive cyber security systems and controls in the AMI environment cannot be done in a "bolt-on" manner**,** nor with "point-to-point solutions". Cyber security solutions must be integrated into all AMI end point components, meters, applications, hosts, and the network infrastructure to be successful.

Our research work on simulation and analysis of attacks on the smart grid demonstrated the need for a multi-layered, integrated modeling approach to enable accurate evaluation of such complex, heterogeneous, system-of-systems. For instance, consider the case of a cyber-physical attack that originates in the cyber domain, and impacts the physical domain. An accurate analysis of such an attack would require a model of the cyber domain, a model of the physical domain, and more importantly a model of the cyber-physical interface that allows the attacks to propagate across the cyber-physical interface. This will require complex cyber security systems integration and analysis of the planned architecture prior to the design phase of the "to be environment", for both domains prior to the full scale implementation.

LADWP must work closely with the selected AMI meter vendors for the full scale deployment and insist they provide them with application programming interfaces (API) to retrieve CGR-meter associations. Detection and diagnosis of certain security threats requires us to correlate data from AMI meters and their corresponding CGRs. For example, to infer a Denial-of-Service attack on a CGR would require us to correlate communication failures from meters behind a CGR, and events from a corresponding CGR. This requires the detection and diagnosis processes to maintain a reliable model of CGR-AMI meter associations in the system.

The AMI infrastructure must provide debugging and diagnostic interfaces (preferably in the form of API's) to easily measure the network latencies in the AMI network. The ability to measure network latencies in a dynamic network is a fundamental tool in the arsenal of a network engineer, and is invaluable for modeling dynamic network behavior for higher-level cyber security reasoning. LADWP must work closely with AMI meter vendors and insist they provide them with these APIs.

Finally, a cyber security test bed environment must be deployed to better demonstrate the effectiveness of the security measures within the Smart Grid architecture. The testbed is also needed for those attacks that

cannot be tested within an active system (e.g. because it requires simulating failures) as well as those for which the scalability of defenses exist beyond the scale of the actual AMI environment.

12 Products Developed

12.1 Patents

No intellectual properties were developed for AMI, DR, CB, or CS in SGRDP. Patent inventions were reported by UCLA for intellectual discoveries for EV. The following inventions were developed under the award:

- Battery Energy Storage Control System
- Intelligentization For Electric Vehicle Charging
- Fast Response Smart Electric Vehicle Charging Software and Control Hardware
- SMERC EV Charging Control System
- Wireless Network (Or Cloud) Based Management of Multiplexed EV Charging Infrastructure
- Intelligent Distributed Low Cost Electric Vehicle Charging System

12.2 Other Products

12.2.1 Computer Models

Following are computer models developed as a result of the EV project:

a) EDD:
   - IEEE 34 Bus System (DEMO #8, #11, #21)
   - USC Microgrid (DEMO #11)
   - Chatsworth Distribution System (DEMO #8, #11)

b) OpenDSS
   - IEEE 34 Bus System (DEMO #11)
   - USC Microgrid (DEMO #11)

c) HOMER
   - USC Microgrid Design and Operation Analysis (DEMO #11)

d) MATLAB
   - EV Charging/Discharging Model to obtain Optimum Flat Load Profile (DEMO #8)
   - Utility - Customer Interface Strategy and User Application for Electric Vehicles and Distributed Generation Management (DEMO #11)

e) PSCAD
   - IEEE 34 Bus System (DEMO #21)

f) PSS/E
   - WECC System (DEMO #20)
   - USC Microgrid (DEMO #11)

g) PSLF
   - WECC System (DEMO #20)

12.2.2 Hardware Requirements

Below is hardware requirements needed to reconstruct computer models for the EV project:

a) OBDLink MX from ScanTool.net: It is used to monitor iMiEV charging and trip information for (DEMO #19)

b) NImyRIO from National Instruments: the initial tool USC utilized to monitor the iMiEV charging and trip information, but it did not work as required in Use Case #19. Therefore, the OBDLink MX tool was used.

There were no hardware requirements were developed as a result of SGRDP as hardware was purchased from the selected Smart Meter vendor for AMI and CB. The hardware purchased for the demonstration can be found in section 9.2.1 Metering System. AMI did not present project results on any internet.

12.2.3. Media

LADWP developed an intranet and internet site https://sgrdp.ladwp.com and https://www.ladwp.com/smartgrid that reflect the result of this project.

Outreach Videos 1-6 were developed to provide short educational/tutorials information that explains the Smart Grid, what is energy sustainability and how consumers can use the Smart Grid to become more energy efficient and informed. Covered topics include:

• The Energy Problem – Describes the challenges of balancing increasing demand against limited and costly resources (both traditional fossil fuel-based and alternative sources) and concerns with the environment.

• Smart Grid & Sustainability – Describes what the Smart Grid is and how the technology contributes to energy sustainability. Also describes the Smart Grid Regional Demonstration project (SGRDP).

•Smart Meters – Describes what a smart meter is in detail, how it works with the Smart Grid and how the information provided by the meter can help consumers become more informed on their energy usage and how to become more energy efficient. Content includes a discussion on data privacy and LADWP's policy.

• What is Demand Response – Describes in the context of the Smart Grid with discussions on peak demand, blackouts/brownouts and voluntary/involuntary curtailment.

• EVs and Smart Grid – Discusses EV technology, the different types of chargers and the impact on the Smart Grid.

• Energy efficiency / customer engagement – Describes how the customer can become more energy efficient and environmentally friendly using Smart Grid and Smart Meters.

Videos can be accessed on

https://www.ladwp.com/ladwp/faces/ladwp/aboutus/a-power/a-p-smartgridla?_adf.ctrl-state=135fl6p99h_35&_afrLoop=79148549466819&_afrWindowMode=0&_afrWindowId=ek7xjp309_1#%40%3F_afrWindowId%3Dek7xjp309_1%26_afrLoop%3D79148549466819%26_afrWindowMode%3D0%26_adf.ctrl-state%3Dek7xjp309_29

12.2.4. Publications

93 peer-reviewed papers resulted from SGRDP were presented at a conference or published between 2010 and 2016. Papers are listed in Appendix AU.

13 Overall Project Conclusion

13.1 Stakeholders Feedback

The meters were traditionally used solely for the purpose of generating bills. Today, however, the smart meters have gone beyond that. For example, the smart meters can provide alarms and alerts to notify utility of undesired conditions. They can also monitor critical aspects of the electric service such as voltage and power quality.

No customer feedback was collected since the portal does not allow customers to provide feedback. The CB team intended to allow customer feedback in design to have them respond to short surveys from Customer Behavior Team inbox, but there was not have enough time in the demonstration to implement the feature.

JPL & ISI CS teams recommended some specific changes to de-couple functions that did not have a real need for the dependencies that were initially designed in, and to re-route some data flows to separate sensitive functions from potentially "dangerous" sources.

13.2 Best Practices

LADWP recommends the following best practices:

- Getting IT and Communications teams involved with the project in the project initiation phase.
- Working out system compatibility as early as possible will greatly streamline development and implementation
- Attend to the meter order process is essential to maintaining schedule and project milestones.
- By mobilizing more resources sooner we would have better met schedule and milestone dates.
- It is critical that a systems integrator be brought on board early on in the project to ensure an end-to-end, interoperable capability in the final product. This would address important issues such as the validation of data to ensure consistency between the production and receipt of data at all the distributed end-points where data is consumed. There should have been a stronger plan for system integration from the start of this project.-

Additional recommendations to address specific types of issues with high impacts to customers and business are shown below.

Budget Management

- Contract budget - USC research Lead cannot hire staff until funding from LADWP is received. Delay impacted USC schedule due to lack of funding to USC. Significant team good will squandered.
    - **Recommendations:** Outline what is reimbursement, what advance notice/approval need to be obtained, and what supporting documents are required for invoices
- Overspent funds - UCLA overspent task orders.

- **Recommendations:** Before deliverables were completed, UCLA overspent budgeted task order for specific deliverables

Influence customer base

- Low customer portal registration/customer uptake. Previously undetected LADWP marketing email "blacklisting" by over 290 ISPs most likely prevented numerous customers from receiving portal outreach emails during Spring 2016 Registration Campaign. In May 2016, as many as 25% of portal customer outreach emails hard bounced. Research shows that customers less willing to adopt new initatives unless incentived to do so; LADWP is limited in its ability to offer incentives because cumbersome approval process crosses multiple departments.
  - **Recommendations:** Ensure outreach channels (email) are functional. Establish process/procedure of all required approval channels to effectively plan outreach. Provide incentives to garner participation in programs. Need to be creative on how incentives are offered.
- Influence customer base - Delayed customer outreach. Smart meter outreach efforts were diluted due to drawn-out meter installation process between 2013-2014. Customers experienced lengthy waits between notification of initial smart meter program launch and actual meter installations. Customers were not engaged early enough or have not been well informed of pilot/technology. DR programs need customers to be involved to execute DR events.
  - **Recommendations:** Prevent unforeseen Customer repercussions by promoting and educating Customer early and often

Project Planning

- Delay in sign off - Portal go live is dependent on CIO sign off. CIO provided sign off, however, now CSD will not sign off until a SLA is in place. Delay in managerial sign-off due to conflict over portal support.
  - **Recommendations:** Identify all sign off process, resources, and contingency in planning stage, Ensure that internal groups will support systems prior to development
- Project control on scope, budget, and schedule- Major milestones were de-scoped due to lack of time/progress. CB and CS demonstrations were removed due to lack of time and recurring need to prioritize/evaluation new approach
  - **Recommendations:** Daily conference calls with the vendor to monitor closely the status of the project, the issues that need to be addressed, and the next steps to be taken.
- Coordination with other dept. - Need clear expectations from each sub-project. Lack of central ‘metering authority’ which impacted various organizations from effectively collaborating with each other to accomplish the mission of the AMI project. Rates are defined by another group other to accomplish the mission of the AMI project.
  - **Recommendations:** Identify and involve all stakeholders early in the project to determine requirements/decision-makers in the planning stage. Getting IT and Communications teams involved with the project in the project initiation phase. Have steady communication between various stakeholders in the form of weekly meetings and conference calls. A central ‘metering authority’ needs to be put in place for various

organizations to effectively collaborate with each other to accomplish the mission of the AMI project. Divide project into project teams for effective results. Have a small group at utility to deal with customer issue (i.e. complaints on AMI meters).

- Lack of documentation - Lack of clear and updated documentations. In-house processes were not defined (i.e. how to get firewalls open), requirements, roles, responsibilities were not clearly defined, testing process not in place, there were no test beds, along with lack support in communication and collaboration resulted to losing time.
    - **Recommendations:** Have clear and updated documentations. Ensure editable project documentations are archived to streamline transition from resource change.
- Infrastructure of MDM - Delays in Meter Data Management (MDM) go-live will impact Meter data storage. Data may not be distributed to the data subscribers and neither commands nor web services can be initiated through the head end.
    - **Recommendations:** Plan thorough initial integration testing and have alternative channel outside of MDM to collect data. For an Advanced Metering Infrastructure system to have its full benefits, the automation needs to be from end to end. This is known in the industry as 'meter to cash' process. Many of technical and societal benefits occur when the data is collected remotely, and disconnect and reconnect of customers also take place remotely. Automating process for the data transmittal to MDM, and transmittal of final bill determinants to the CIS systems also add to the benefits. In other words: the more of processes get automated, the more of benefits get experienced through time.
- Scope - Various loading scenarios was not realistic. The design document requirement to construct LADWP infrastructure network for the system analysis for this use case was not realistic.
    - **Recommendations:** Determine realistic capability when developing scope.

13.3 Long term Implementation forecast

LADWP's long-term implementation goal is to install a comprehensive SG throughout its service territory over the next 10-15 years. The implementation plan will benefit from the SGRDP lessons learned and contribute to best practices for AMI deployment. The program will be implemented in Stages, first building on the lessons learned in the Department's early smart grid pilots, and then evolving to the construction of the smart grid foundation – the Advanced Metering Infrastructure (AMI). Subsequent Stages will deliver advanced smart grid operational capabilities and enhanced customer programs and services.

Stage 1: Pilots (2010 – 2016)

Comprised of early efforts by the LADWP to demonstrate and learn from initial limited deployments of advanced meters, demand response mechanisms, cyber security, and renewable energy and electric vehicle integrations. These efforts are predominantly complete and have yielded the insights and experiences needed to develop the vision and roadmap.

Stage 2: AMI Foundation (2016 – 2022)

This implementation effort for a foundational Advanced Metering Infrastructure (AMI) system will complete the system wide deployment of smart meters and the underlying network communication backbone, and initiate broader offerings of demand response and other customer programs. This

foundation will enable several new capabilities, and will provide a platform for several of the initiatives planned in Stage 3.

Starting in 2017, LADWP will replace approximately 1.5 million traditional, electric meters with digital, two-way communicating smart meters. Legacy mechanical meters served the Department well, but lack the advanced capabilities of smart meters – which act as intelligent endpoints – establishing a two-way relationship with each residential and business customer served by LADWP.

The initial focus will be on the back office systems and communication infrastructure needed to support a series of phased implementations of specific AMI-related and grid modernization applications.

By constructing an AMI deployment plan around a series of phased AMI-related application implementations, LADWP will be able to realize immediate value from its initial smart meter deployments. Criteria for rollout led to the process of phased installations by district. Subsequent deployments will focus on market areas that are most likely to generate additional value from customer prepayment and demand response programs.

Smart meters enable two-way communication between customers and the Department. They capture, record, and transmit key data, such as electricity usage, in intervals, which provides the granular data needed to help customers better manage their electric usage and costs, and provides a foundation for developing new, intelligent, and customized energy efficiency and demand response programs. Through this communication technology, the Department will improve overall billing accuracy, minimize estimated bills, provide customers access to their usage information throughout the billing period, implement monthly billing, and identify power outages more quickly and accurately. Smart meters are also equipped with an integrated remote service switch, which allows service connections and disconnections to be performed remotely, over-the-air at the customer's convenience.

LADWP can use the real-time energy usage and pricing data becoming available to LADWP and its ratepayers for grid optimization, market-based pricing, and improvements in efficiency, reliability, and power quality. AMI can provide the capability for automated metering of time-stamped power at various locations (campus, residential, commercial and industrial) and power quality monitoring at select locations, and for transmitting that metered data by way of secure public and private communication networks to the LADWP back office for billing and maintenance purposes.

LADWP's subsequent AMI deployment outlook plans to focus on the highest-impact opportunities (i.e., areas with high usage/high turnover) in order to better manage initial investments and to accelerate and maximize benefit capture.

Other long term performance forecast considerations for AMI:

• Stage the deployment of the AMI meters that allow LADWP to maximize the useful life of its existing ERT and conventional electromechanical meters, while preserving as much backwards and open/multivendor compatibility as possible with any future AMI deployments.

• Adapt to changing priorities as additional project stages evolve and new opportunities are identified.

• Phase-in subsequent deployments of advanced-functionality AMI assets in a manner that create opportunities and mitigate risks (i.e., technology changes) to expand the deployment to additional alternate areas.

• Maintain a financial position and reduce future schedule and budgetary risks by optimizing the capital investment profile and maximizing the return on initial investments.

LADWP intends to give preference to those technologies identified by the Smart Grid Interoperability Panel in their Catalog of Standards. However, each technology used in the LADWP network shall also be individually reviewed by LADWP for the following characteristics:

- Level of Standardization
- Level of Openness
- Level of Adoption
- Level of Users Group Support
- Security
- Manageability
- Scalability
- Use of Object Modeling
- Use of Self-Description and Metadata
- Use elsewhere in the Power Industry

In cases where open standards are still under development or not sufficiently interoperable, LADWP may take one or more of the following actions:

- Defer some functionality of a project until an open interoperable standard is available
- Require that vendors commit to a seamless upgrade to a standard when one is available
- Participate in a standards development process to accelerate its development

Stage 3: Integration and Optimization (2018 – 2025)
Building on the foundation deployed during Stage 2, the LADWP will deploy a series of technologies and programs that will leverage the AMI system, optimize the integration of these various new capabilities, and prepare for the initiatives anticipated in Stage 4.

Stage 4: Modernized Grid (2022 – 2030)
In the subsequent decade, the Department will introduce highly distributed intelligent controls that will increasingly involve automated transactions. This Stage will include wider deployments of distributed computing technologies for faster system response times, the integration of additional sensors and controls, and the ability to manage and react to supply and demand imbalances at the micro level.

LADWP will need to access real-time data and have the ability to access recorded data to make better decisions, such as forecasting demands, billing forecasts, shaping customer usage patterns, and preventing electric outages. To make those decisions, the system will need to store large amounts of data, and have the ability to process and manage that data.

This phased, priority-driven deployment of the more advanced functionalities at the highest-impact locations, and on a timetable which makes technical and economic sense will increase the likelihood of a successful deployment and integration of a full-scale deployment.

LADWP is looking to expand the CB portal to include water meters. The CB portal will be used to perform demand response with commercial OpenADR events. USC has already signed up to participate in 2016 DR events and committed to curtail 1.25MW. Additional deployed technologies and systems for DR and EV will remain in production for data collection as the developed DDS can perform continuous learning and is able to scale to more customers using reasonable computation hardware and can be integrated with other components such as FMS Information & Control Systems, customer behavior models and DWP Software Stack. The collected data can be used to better enhance guidance for future system development at LADWP and other utilities on distribution system reliability, asset management, infrastructure optimization, and cost effectiveness.

13.4 Life Time Performance Benefit

In the interest of using a common set of benefit categories and methodologies that is unbiased, clear and easily understood, the LADWP chose to model its benefits framework after the benefits evaluation model that EPRI included in the report titled "Methodological Approach for Estimating the Benefits and Costs of Smart Grid Demonstration Projects."

Benefit Category	Description of Benefits
Economic	Remote meter reading eliminates the cost of sending personnel to each meter to read the meter manually.
Economic	Advanced meters are more accurate at low consumption levels than traditional meters, permitting revenue from previously unaccounted-for energy usage.
Economic	An integrated advanced metering infrastructure can eliminate labor-intensive steps in the processing of usage data and the production of bills.
Economic	By remotely connecting and disconnecting electrical service, LADWP can avoid the costs of sending personnel to the customer site for this purpose.
Economic	Remote disconnects for non-payment can be performed more quickly, reducing the amount of uncollectible revenue.
Economic	Giving customer service representatives the ability to immediately perform start and stop service requests may reduce the number of calls currently received from customer checking on scheduled connects and disconnects, and will provide greater customer satisfaction.
Economic	The capability of meters to immediately report tampering to the utility may cause theft to be detected more often, do so earlier before the theft occurs, and may

Benefit Category	Description of Benefits
	reduce the time and effort required to investigate and correct the theft. The awareness of this capability may act as a deterrent to theft.
Economic	The ability to remotely analyze metering data for theft patterns may reduce the number of site visits necessary for physical examination of meters, and may detect theft that would otherwise go unnoticed.
Economic	Remote automatic meter reads can improve the customer service experience by avoiding property issues and billing errors. Many customer service calls are related to high bill complaints. Providing customers with data and information that provides insight into their energy consumption prior to bills being issued will reduce the number of bill complaint calls. This benefit impacts both parties financially, and also saves customers time to resolve such issues.
Reliability	The automatic reporting of power outages to individual meters will allow LADWP to more quickly narrow the location and potential cause of outages independent of customer outage reports, reducing the duration of outages.
Reliability	Reliability indices calculations such as SAIFI and SAIDI can be improved in accuracy and turnaround.
Reliability	Improvements to distribution planning due to greater visibility of customer load.
Environmental	The potential to reduce emission with fewer truck rolls for meter reading/ field services activities.
Environmental	The potential to reduce emission with reduced energy usage due to conservation.
Regulatory	The Smart Meter and AMI systems can also enable Time-of-Use, Dynamic Pricing, and other tariff schemes. Changes in market rules can result in significant changes to power demand and supply. Regulatory approval will be necessary.
Societal & Other	Providing timely consumption information to customers and making use of the ability to support time-of-use rates may reduce demand at peak times of the day, eliminating costly peaking generators or energy purchase to meet peaks.
Societal & Other	Customers have increased confidence in billing accuracy based on the metering system utilizing real-time data from the AMI system.
Societal & Other	Customer bill amount reduction.
Societal & Other	Increased customer satisfaction by providing customers with new detailed information related to their usage.

Benefit Category	Description of Benefits
Societal & Other	By reducing the need to dispatch LADWP personnel into the field, workers are at less risk of motor vehicle accidents and other potentially dangerous incidents.
Societal & Other	This project enables the benefits of the other projects in the AMI work stream.

Table 74:Benefits of Enhanced Metering, Customer Information and Rates

Benefit Category	Description of Benefits
Economic	Reduces peak demand and therefore avoids the costs of adding the capacity necessary to serve the maximum load.
Economic	Improves the efficiency of existing generation by charging PEVs at low usage time, lowering the cost per unit of power delivered.
Economic	To the extent that ancillary services provided by PEVs offset fossil generation, additional renewable energy credits could be captured.
Economic	Shifting PEV charging to off-peak hours can potentially provide LADWP with additional margin on energy sales.
Reliability	Potentially applying utility controls to PEVs to: Apply Ancillary Services to grid Optimize PEV charging
Reliability	Use of PEVs for Frequency Control can reduce local outages on distribution feeders.
Reliability	Potentially avoid distribution overloads, and local over/under-voltage outages and flicker events on distribution feeders.
Reliability	Permits study and monitoring of PEV charging behavior and subsequent improvement of the power system, regulation and rates to deal with PEV use.
Environmental	The utilization of PEVs to provide ancillary services can reduce the operation of fossil fueled generation units to provide the same services, lowering carbon emissions.
Regulatory	AB 32 encourages increased electrification of vehicles as a means to reduce GHG emission.
Societal & Other	Customers may have the opportunity to receive incentives for participating in advanced PEV programs which provide ancillary services.

Table 75: Benefits of DR and DER Integration Programs

Benefit Category	Description of Benefits
Reliability	Improved modeling and planning capabilities associated with managing distributed generation would allow LADWP to: Identify problematic circuits/feeders Provision additional devices and advanced devices such as intelligent transformers Include stability features which would reduce local outage incidents on distribution feeders
Regulatory	Using better forecasting, energy management applications and storage sources, LADWP can increase the utilization of the intermittent renewable sources. Increased usage of renewable energy will help meet RPS regulatory goals including SB2's goal of 25% in 2016, 33% in 2020 and 50% in 2030.

Table 76: Benefits of Enhanced Forecasting of Renewable Generation

Benefit Category	Description of Benefits
Economic	DR programs can reduce peak demand and therefore the capacity requirement necessary to serve the maximum load. This can help avoid or defer additional investments required to serve increased load in the future, including new generation, transmission, or distribution capacity.
Economic	Dispatching DR on congested distribution circuits can defer upgrading the distribution network.
Economic	LADWP may have the opportunity to aggregate and trade DR services in CAISO's market.
Reliability	Targeting specific customers for demand response can help to avoid reliability problems due to overloading of particular circuits.
Reliability	If enrollment is widespread enough, geographically aggregated demand response can be used in real-time to prevent outages by reducing load when there is a danger of overload, without causing blackouts as in the case of traditional load shedding.
Environmental	Potentially avoid the use of more expensive imported energy or local high-emission peaking generation (e.g. Haynes Unit 6).
Regulatory	Improve the grid operators' ability to respond to conditions that could lead to generator tripping or other outages.
Societal & Other	Customers may consume less energy or modify their behavior as a result of new information from smart grid programs. Their total cost of electricity may be reduced from such changes.
Societal & Other	Customers may receive incentives (monetary or other) for participation in certain programs such as Direct Load Control.

Benefit Category	Description of Benefits
Societal & Other	Customers are often willing to participate in programs where they feel they are making a positive difference.

Table 77: Benefits of Demand Response (Small Customer)

Benefit Category	Description of Benefits
Economic	DR programs can reduce peak demand and therefore the capacity requirement necessary to serve the maximum load. This can help avoid or defer additional investments required to serve increased load in the future, including new generation, transmission, or distribution capacity.
Economic	Dispatching DR on congested distribution circuits can defer upgrading the distribution network.
Economic	LADWP may have the opportunity to aggregate and trade DR services in CAISO's market.
Reliability	Targeting specific customers for demand response can help to avoid reliability problems due to overloading of particular circuits.
Reliability	If enrollment is widespread enough, geographically aggregated demand response can be used in real-time to prevent outages by reducing load when there is a danger of overload, without causing blackouts as in the case of traditional load shedding.
Environmental	Potentially avoid the use of more expensive imported energy or local high-emission peaking generation.
Regulatory	Improve the grid operators' ability to respond to conditions that could lead to generator tripping or other outages.
Societal & Other	Customers may consume less energy or modify their behavior as a result of new information from smart grid programs. Their total cost of electricity may be reduced from such changes.
Societal & Other	Customers may receive incentives (monetary or other) for participation in certain programs such as Direct Load Control.
Societal & Other	Customers are often willing to participate in programs where they feel they are making a positive difference.

Table 78: Benefits of Demand Response (Large Customer)

Benefit Category	Description of Benefits
Economic	Across LADWP's customer base, prepayment program adoption will reduce overall time to collect revenue. (In industry citations, up to 10% of consumers adopt prepayment within 6 months and may reach as high as 20% after 2 years). By collecting payments before service is provided instead of after, LADWP will enhance the time value of its cash flow.
Economic	LADWP can reduce time-to-collect by putting frequent late-paying customers on prepayment plans. This can help make cash flow more predictable.
Economic	LADWP can improve cash flow by putting risky (high default probability) customers on prepayment plans and thereby reducing write-offs.
Economic	Prepayment may result in a reductions of deposits, credit checks, bad debt, call center activity, write offs, paper bills, disconnect notices, field collections, and truck rolls for disconnect/reconnect.
Environmental	To the extent that customers participating in a prepayment program reduce their consumption of energy, there would be a corresponding reduction in carbon emissions.
Environmental	Reduction in field crew travel to support disconnects/reconnects will reduce vehicle emissions.
Societal & Other	Customers participating in prepayment programs typically reduce their overall consumption of energy. This results in a reduced cost benefit for the customer.
Societal & Other	Prepayment programs can result in increased customer satisfaction.
Societal & Other	By decreasing LADWP personnel field work, workers are at less risk of motor vehicle accidents and other potentially dangerous incidents.

Table 79: Benefits of Customer Prepayment

Benefit Category	Description of Benefits
Economic	Automated voltage and VAR control eliminates the need to send a field worker to the location of reactive devices in order to operate them. Reactive power resources include capacitor banks, voltage regulators, transformer load-tap changers, storage and distributed generation (DG).
Economic	Coordinating the settings of voltage control devices can ensure that customer voltages remain within service tolerances, and minimize the amount of reactive power provided. Doing so can improve the power factor and reduce line losses for loads.

Benefit Category	Description of Benefits
Economic	These improvements will provide LADWP with the ability to easily maintain regulatory voltage requirements without incurring the costs of sending personnel to site to operate reactive power resources.
Economic	Remote monitoring and control of transformer load tap changers and capacitor banks will enable optimization and tracking of mechanism operations to minimize the number of operations, support maintenance scheduling, and optimize equipment life.
Economic	Remote monitoring of feeder based devices such as capacitor bank controls will also confirm that the devices and in particular the batteries are working properly or require servicing. Since batteries are prone to failure over time, this monitoring capability could have a significant impact on the effectiveness of the volt/VAR control system and reduce maintenance costs.
Economic	Significant energy savings and accompanying cost savings can be achieved by lowering overall system voltage by very small amounts. For instance, lowering voltage by 3 volts can result in 2.4% energy savings, with a corresponding lowering of emissions.
Reliability	Using AMI data, reactive power resources can be better coordinated to reduce active and reactive power requirements from generation.
Reliability	Automated control systems perform a "self-healing" function improving reliability factors that could otherwise have led to outages.
Reliability	Enhanced power quality and voltage monitoring can allow LADWP to identify equipment problems before they cause outages.
Environmental	Energy reductions achieved through improved efficiency and energy conservation voltage reduction will reduce the amount of generation required to serve load. Assuming that the generation is fossil-based, emissions will be reduced.
Regulatory	High penetration solar distributed generation and the use of electric vehicles will have significant impacts on system voltage. These impacts will change dynamically and not be predictable in the way that voltage changes can currently be predicted from weather measurements and past performance. The output of grid-connected solar will be reduced if distribution voltages are not managed adequately. This will reduce the contribution of these resources towards meeting RPS goal. Therefore it is important to have a means to react to dynamic voltage changes.
Reliability	Staggered read of AMI data can help in destiny delayed voltage recovery (FIDVR)
Societal & Other	Customers with grid tied solar will see greater output if the voltage level is maintained below the IEEE 1547 cutoff level
Societal & Other	Identification of unintentional islanding. Incorporate pervasive censoring into safety practices.

Benefit Category	Description of Benefits
Societal & Other	Reduction in truck rolls for equipment inspections and change of device settings will result in minimizing accidents.

Table 80: Benefits of Voltage and VAR Control

Benefit Category	Description of Benefits
Economic	Discovery of limited capabilities may prevent physical damage of equipment and may extend the asset's life. The need for upgrading and replacing equipment may also be determined sooner and possibly avoiding future failures. Factors may include: impedance, ambient temperature, and wind speed.
Economic	Online diagnosis and reporting of equipment condition would reduce the number of on-site inspections required for transformers.
Economic	LADWP may incur legal claims costs associated with asset failure-related outages. These costs could be reduced with better information related to asset condition.
Economic	Improved information on asset status and dynamic asset capacities (especially on 500 kV transformers and lines) can increase utilization of those assets and reduce the potential of taking a 500 kV line out of service unnecessarily and avoiding utilization of local, higher-cost generation.
Reliability	By utilizing on-line diagnosis and reporting of equipment condition, LADWP could identify equipment problems before they cause outages. Improved speed and accuracy in outage notification to grid managers can reduce time to start restoration actions.
Environmental	Improved information on asset status (especially on 500 kV transformers) can reduce the potential of taking a 500 kV line out of service unnecessarily and avoiding utilization of local generation and associated emissions in LA basin.
Regulatory	Better and more timely information on asset status and failures can reduce the potential for reliability- and operations-related fines imposed by NERC.
Societal & Other	By utilizing on-line diagnosis and reporting of equipment condition, LADWP could identify and mitigate equipment problems that could otherwise result in hazardous conditions.

Table 81: Benefits of Asset Condition Monitoring

Benefit Category	Description of Benefits
Economic	Renewable programs can reduce peak demand and therefore the capacity requirement necessary to serve the maximum load.
Economic	Remote control of distributed generation resources using smart inverters can permit LADWP to adjust voltage, frequency, and reactive power on distribution circuits to improve reliability and customer satisfaction, and potentially participate in ancillary service markets.

Benefit Category	Description of Benefits
Reliability	The capability to remotely monitor and manage distributed generation will enable LADWP to increase the level of renewable generation resources in the power network while maintaining reliability.
Reliability	The use of smart inverters at distribution generation sites can enable LADWP to better monitor distribution circuits, improve power quality, adjust voltage, adjust frequency, and control the reactive power level on the circuit.
Environmental	Renewable energy resources have a lower carbon footprint and lower GHG Overall reduction in carbon dioxide (CO_2) emissions, the principal gas associated with global warming. LADWP support will increase renewable energy and further reduce GHG. Renewable energy resources generation produces no NO_x or SO_x air pollutants. Increased renewable penetration further improves air quality. Distributed Generation Monitoring and Control will enable integration of energy from renewable resources.
Regulatory	Senate Bill (SB) 2 (1X) requires 33% Renewable Portfolio Standard (RPS) by 2020.LADWP has committed for 35% RPS by 2020.
Social & Other	Increased local solar power will meet public's preference. Public inputs indicate that increased local solar generation is desired.
Social & Other	Customers may have the opportunity to receive incentives for participating in Solar Installation programs.
Social & Other	Customers who install solar systems will lower their total cost of electricity.

Table 82: Benefits of Generation Monitoring and Control

Benefit Category	Description of Benefits
Economic	Enabling the advanced EMS applications that are currently not used by LADWP can greatly improve operators' ability to react to critical situations. This will result in safer operation and quicker resolution of reliability problems despite the expected introduction of new, variable generation sources to the system.
Economic	Enhanced operating information enables better coordination between regional power grids, and can reduce the need for conservative ancillary service levels.
Reliability	Using phasor data to generate more accurate impedance information could improve the fault location identification process, reducing the duration of outages.

Benefit Category	Description of Benefits
Reliability	More comprehensive real-time monitoring and dynamic line rating algorithms enable operators to raise the stability limit of transmission lines, thereby reducing congestion.
Reliability	Online contingency analysis enables operators to react more quickly to critical situations. It provides a more effective way to address nested or cascading failures by presenting operators with alternate choices for action that are appropriate to the current state of the system even as that state changes.
Reliability	An online EMS training simulator permits operators to learn how to identify and react to time-critical reliability problems as they would appear in the real network and observe the results of their actions presented in a realistic manner.
Reliability	An enhanced power system state estimation application making use of phasor measurements can enable operators to observe the voltage and current waveforms of the bulk power system at very high levels of detail. This capability provides deeper insight into the real-time stability of the power system, and the effects of generator dispatch and operation. It will allow operators to potentially optimize individual generators, and groups of generators, to improve grid stability during conditions of high system stress.
Environmental	Improved information on system state will allow operators to avoid unnecessary utilization of local generation and associated emissions in LA basin.
Regulatory	Maintain compliance with NERC requirement. Contributes to LADWP's status in the top quartile of reliable power providers.

Table 83: Benefits of Enhanced System Operations

Benefit Category	Description of Benefits
Economic	Accurate loading data from the AMI system and transformer “odometer” calculations can permit planners to move oversized transformers on low-load circuits to where they are better utilized, to move overloaded transformers to areas with less load, to load existing transformers more fully with more confidence in their limits, and to choose the capacity of new transformers so they are sized less wastefully. Discovery of higher capabilities may raise stability limits and allow for deferred investments. Capability factors may include: impedance, ambient temperature, wind speed.
Economic	Discovery of limited capabilities may prevent physical damage of equipment and extend asset life. Need for upgrades and replacements may also be determined sooner and failures avoided. Factors may include: impedance, ambient temperature, and wind speed.
Economic	With improved knowledge of the electrical system and accurate electrical models, grid operators can potentially optimize generator dispatch and operation.

Benefit Category	Description of Benefits
Reliability	Proactively predicting failure and replacing overloaded transformers before the beginning of heat storm season may reduce the number of unplanned outages due to the large number of transformers lost each season. The current program replaces 3,000 of over 120,000 transformers per year. More detailed modeling allows the most frequently overloaded 3,000 transformers to be replaced rather than using other less useful criteria.
Reliability	Regular loading reports and real-time estimates driven by AMI data permit planners and operators to prevent unexpected overloads due to the variability of load from EVs and production from renewable generation.
Regulatory	An accurate electrical model is an important prerequisite for integration of distributed energy resources on LADWP's system at the 33-35% levels as required by the City and LADWP's IRP. Awareness of the location and size of these resources is essential for accurate load/resource planning and for maintaining system reliability and stability.
Reliability	Fault indicators and remote operated switches perform a "self-healing" function improving reliability factors that could otherwise have led to outages.
Environmental	With improved knowledge of the electrical system and accurate electrical models, grid operators can avoid unnecessary utilization of local generation and associated emissions in LA basin.
Social & Other	An accurate system model will improve customer service by enabling customer representatives to have updated system information.
Social & Other	An accurate model provides a safer working condition by making updates to systems and conditionally available to field crew.

Table 84: Benefits of Distribution System Modeling, Planning and Automation

14 Acknowledgements

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This Cyber Security work was carried out by LADWP Information Technology Services (ITS), and by the Jet Propulsion Laboratory (JPL), California Institute of Technology, under a contract with the Los Angeles Department of Water and Power.

15 Appendices

Appendix A Acronyms

Acronyms	Definition
AAC	Authorization and Access Control
AC	Alternating Current
ADR	Automated Demand Response
AES	Advanced Encryption Standard
AFICK	Another File Integrity Checker
AHU	Air handing unit
AMI	Advanced Metering Infrastructure
API	Application Programming Interface
B2G	Building-to-Grid
BAS	Building Automation System
BAN	Building Area Network
BESS	Battery Energy Storage System
BEV	Battery Electric Vehicle
CB	Customer Behavior
CC&B	Customer Care & Billing
CCF	Campus Consumption Forecasting
CE	Collection Engine
CEI	Commercial Energy Information
CES	Community Energy Storage
CG-NMS	Cisco Grid-Network Management System
CGR	Cisco Connected Grid Router
CHADeMO	Charge to move
C&I	Commercial & Industrial

CII	Commercial, Industrial and Institutional
CIS	Customer Information System
COT	Commercial off-the-shelf
CS	Cyber Security
DA	Distribution Automation
DCFC	Direct Current Fast Charge
DDR	Detection, Diagnosis, and Remediation
DDS	Demand response Decision Support
DE-FOA	Department of Energy-Federal Opportunity Announcement
DER	Distributed Energy Resources
DETER	Defense Technology Experimental Research
DEW	Distribution Engineering Workstation
DG	Distributed Generation
DMS	Distribution Management System
DoE	Department of Energy
DR	Demand Response
DRAS	Demand Response Automation Server
DTM	Distribution Transformer Monitor
ECC	Energy Control Center
EDD	Electrical Distribution Design is a power system analysis and simulation software
EMS	Energy Management Systems
EPRI	Electric Power Research Institute
EV	Electric Vehicle
FCR	Fault Containment Region

FIPS	Federal Information Processing Standard
FiT	Feed-in-Tariff
FMS	Facilities Management Services
FOA	Federal Opportunity Announcement
G2B	Grid-to-Battery
G2V	Grid-to-Vehicle
GHG	Green House Gas
GTI	Grid Tied Inverter
GTR	Global Temperature Reset
HAN	Home Area Network
HEI	Home Energy Information
HEM	Home Energy Management
HOMER	Hybrid Optimization Model for Electric Renewables
HTML	Hypertext Markup Language
HVAC	Heating Ventilating and Air Conditioning
ICE	Internal Combustion Engine
ICS	Itron Cellular Solution
IDS	Intrusion Detection System
IEEE	Institute of Electrical and Electronic Engineers
IPS	Intrusion Prevention System
IRP	Integrated Resources Plan
IVR	Interactive Voice Response
JACE	Java Application Control Engine
JPL	Jet Propulsion Laboratory
JSON	JavaScript Object Notation

kW	Kilowatt
kWh	Kilowatt hour
LADWP	Los Angeles Department of Water and Power
LED	Light-emitting diode
LRC	Lyons Recreational Center
LVL	Leavy Library
MATLAB	Matrix Laboratory
MDM	Meter Data Management
NASA	National Aeronautics and Space Administration
NIST	National Institute of Standards and Technology
NISTIR	National Institute of Standards and Technology Interagency Report
NIST SP	National Institute of Standards and Technology Special Publication
NMS	Network Management System
NTP	Network Time Protocol
OMS	Outage Management System
OSB	Oracle Service Bus
PEV	Plug-In Electric Vehicle
PHEV	Plug-In Hybrid Electric Vehicle
PNNL	Pacific Northwest National Laboratory
POLA	Port of Los Angeles
PON	Power Outage Notification
PQ	Power Quality
PRN	Power Restoration Notification
PSCAD	Power System Computer Aided Design
PV	Photovoltaic

PV2G	Solar to grid
PV2B	Solar to battery
PV2EV	Solar to EV
REST	Representational state transfer
RF	Radio Frequency
RFID	Radio Frequency Identification
RFP	Request For Proposal
RPS	Renewable Portfolio Standard
RRE	RF Range Extender
SA	Sbubstation Automation
SCADA	Supervisory Control and Data Acquisition
SG	Smart Grid
SGG	Smart Grid Gateway
SGOC	Smart Grid Operations Center
SGRDP	Smart Grid Regional Demonstration Program
SIEM	System Information and Event Management
SIP	Solar Incentive Program
SOC	State of Charge
SOPO	Statement of Program Objectives
TOU	Time of Use
UART	Universal asynchronous receiver/transmitter
UCLA	University of California, Los Angeles
USC	University of Southern California
V2G	Vehicle-to-Grid
VAR	Volt-Amp Reactance

VAV	Variable Air Volume
VFD	Variable Frequency Drive
VLAN	Virtual Local Area Network
VSOE	Vendor-specific objective evidence
WAN	Wide Area Network
Wi-Fi	Wireless Fidelity
WMIS	Work Management Information
WYE	(Y) configuration is when the phase current and line current are equal
XML	Extensible Markup Language
XRT	Experimental Real-time

Appendix B Contacts

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Susan Miltenberger	U.S. DOE/NETL – Administrator	(304) 285-4083

Appendix C References

Document	Date
Statement of Project Objectives (SOPO)	6/21/2010
Instructions For Preparation of Deliverables for Cooperative Agreements Under the Smart Grid Demonstration Program	1/18/2013
Smart Grid Demonstration Program Guidance for Technology Performance Reports	6/17/2011
Guidebook for ARRA Smart Grid Program Metrics and Benefits—Smart Grid Demonstration Project	12/7/2009
LADWP Smart Grid Regional Demonstration Program Project Management Plan (PMP)	4/14/2013
SGRDP Design - Chapter 1 Overarching (for DoE Submission) v1.0	3/31/2012
SGRDP Design - Chapter 2 AMI (for DoE Submission) v1.0	3/31/2012
SGRDP Design - Chapter 3 CB (for DoE Submission) v1.0	3/31/2012
SGRDP Design - Chapter 4 DR (for DoE Submission) v1.0	3/31/2012
SGRDP Design - Chapter 5 EV (for DoE Submission) v1.0	3/31/2012
SGRDP Design - Chapter 6 CS (for DoE Submission) v1.0	3/31/2012
LADWP Smart Grid Regional Demonstration Project Metrics and Benefits Reporting Plan	6/27/2011
Methodological Approach for Estimating the Benefits and Costs of Smart Grid Demonstration Projects	January 2010
Los Angeles Department of Water and Power Demonstration Project Quarterly Build Metrics Report	June 2016

Appendix D AMI Technical Performance Report

Scope: This report indicates the status of the Technical Performance of the Advanced Metering Infrastructure (AMI) of the LADWP's Smart Grid Regional Demonstration Program (SGRDP), per the Demo Matrix and SOPO documents.

Note: Most of the following actions/demonstrations have been performed many times due to the nature of the operation of a metering system. The occasions described below have been recorded for the purpose of reporting.

Part 1: Metering Data Collection

1. **Collect 15-minute KWH load profile data, as well as all the configured registers, such as KWH (Display 39) and KW Demand (Display 41), and events/alarms, such as high voltage and Last Gasp.**

   Action: 2 EV meters were selected for this test and included as part of the Acceptance Test Group
   1) 2.16.840.1.114416.1.24.1498842
      Badge: 7FED00009-01498842
   2) 2.16.840.1.114416.1.24.1498892
      Badge: 73FED00009-01498892

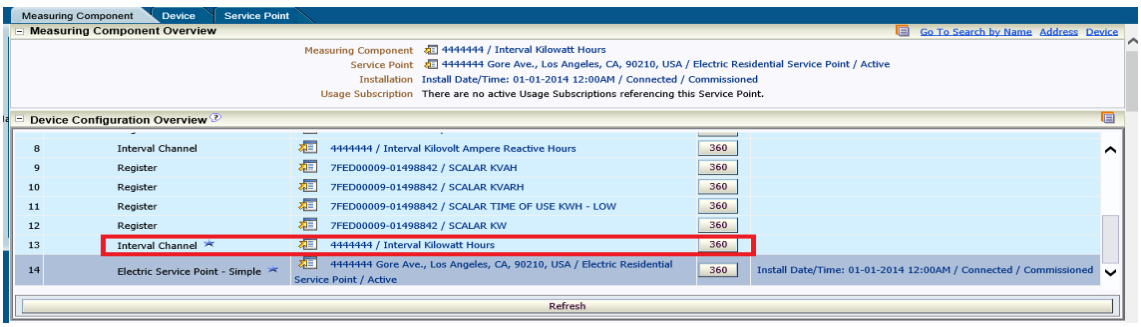
   Acceptance Criteria: Metering data to be collected successfully from at least 95% of tested meters. A 'read' is considered 'successful' when all load profile data, register data, and events/alarms are collected successfully
   Date: 9/10/2014 & 10/3/2014
   Results: Passed, per the following outcomes:

4 EV Meters that were part of Acceptance Test

1) 2.16.840.1.114416.1.24.1498842
   Badge: 7FED00009-01498842
   Itron SN: NXF312197831

Figure 1: Interval Kilowatt Hours

Attached sample



data showing the reads with excel export

Measurement	Measurement Date/Time
KWH	
0.001	10-03-2014 01:15PM
0.003	10-03-2014 01:00PM
0.003	10-03-2014 12:45PM
0.005	10-03-2014 12:30PM
0.005	10-03-2014 12:15PM
0.002	10-03-2014 12:00PM
0.004	10-03-2014 11:45AM
0.006	10-03-2014 11:15AM
0.003	10-03-2014 10:45AM
0.005	10-03-2014 10:15AM
0.006	10-03-2014 10:00AM

Figure 2: Sample data

Results for Scalar KW

Measurements

Measurement Date/Time	Measurement
	KW
10-12-2014 01:00PM	-0.051000
09-22-2014 09:30AM	0.001000
09-15-2014 09:45AM	0.000000
09-09-2014 09:45AM	0.053000
09-02-2014 04:30PM	0.000000

Figure 3: Scalar kW

2) 2.16.840.1.114416.1.24.1498892
   Badge: 73FED00009-01498892 - Itron SN: NXF312197984

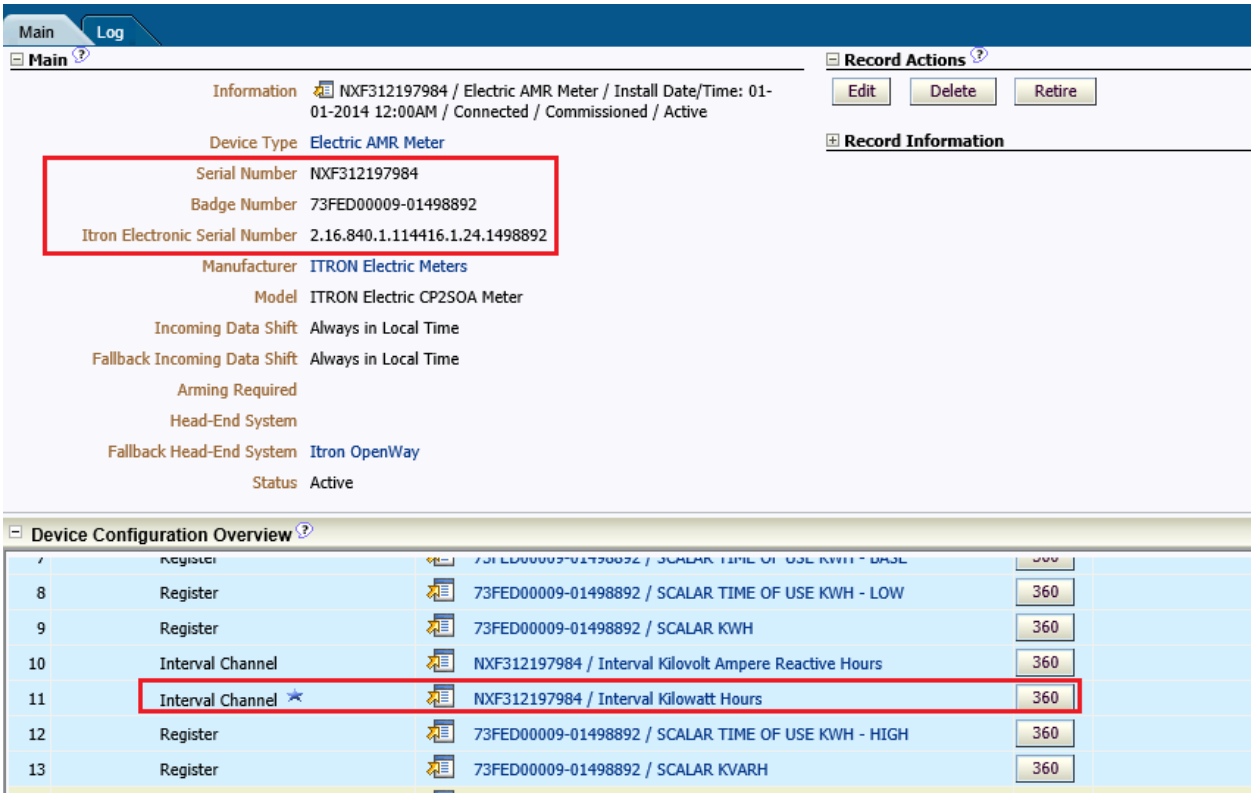


Figure 4: Device Configuration Overview

Attached sample data showing the reads for 9/30 & 10/3 with excel export

Measuren	Measurement Date/Time
KWH	
0.006	10-03-2014 01:15PM
0.005	10-03-2014 12:45PM
0.006	10-03-2014 12:30PM
0.005	10-03-2014 12:00PM
0.01	10-03-2014 11:30AM
0.011	10-03-2014 11:15AM
0.013	10-03-2014 10:45AM
0.013	10-03-2014 10:30AM
0.005	10-03-2014 10:15AM
0.005	10-03-2014 10:00AM
0.005	10-03-2014 09:45AM
0.005	10-03-2014 09:30AM
0.004	10-03-2014 09:15AM
0.005	10-03-2014 09:00AM
0.005	10-03-2014 08:45AM
0.005	10-03-2014 08:00AM

Figure 5: Sample data – reads

Results for Scalar KW

Measurement Date/Time	Measurement
	KW
10-11-2014 09:30AM	0.337000
09-08-2014 10:45AM	0.000000

Figure 6: Results for Scalar kW

2. **Issue the "read" command once every 15 minutes and record the observation.**

   Action: 2 EV meters were selected for this test and included as part of the Acceptance Test Group
   1) 2.16.840.1.114416.1.24.1498842
      Badge: 7FED00009-01498842
   2) 2.16.840.1.114416.1.24.1498892
      Badge: 73FED00009-01498892

   Acceptance Criteria: Metering data to be collected successfully from at least 95% of tested meters. A 'read' is considered 'successful' when all load profile data, register data, and events/alarms are collected successfully

   Date: 9/10/2014 & 10/3/2014

   Results: Passed, based on following outcomes

4 EV Meters that were part of Acceptance Test

1) 2.16.840.1.114416.1.24.1498842
   Badge: 7FED00009-01498842
   Itron SN: NXF312197831

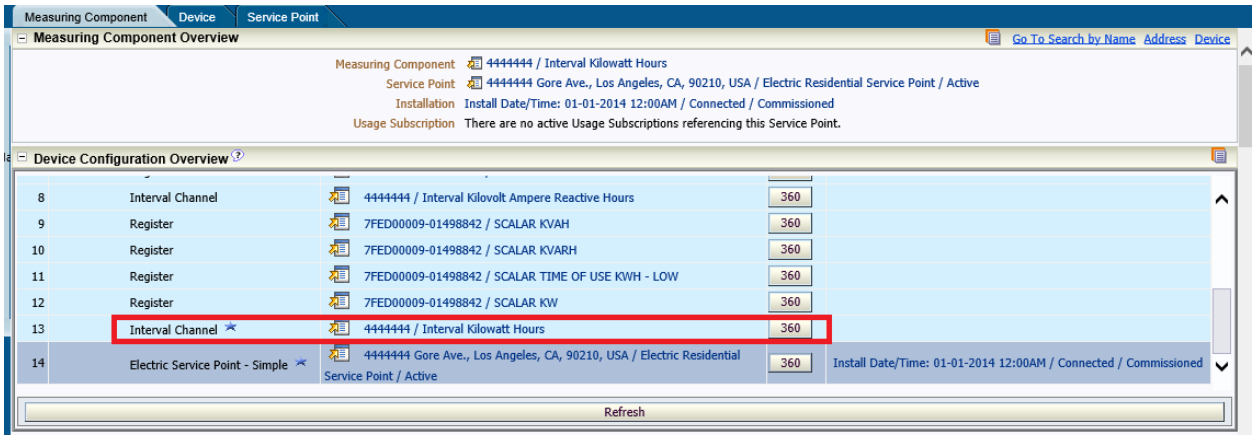


Figure 7: Interval Channel

Attached sample data showing the reads with excel export

Measurement	Measurement Date/Time
KWH	
0.001	10-03-2014 01:15PM
0.003	10-03-2014 01:00PM
0.003	10-03-2014 12:45PM
0.005	10-03-2014 12:30PM
0.005	10-03-2014 12:15PM
0.002	10-03-2014 12:00PM
0.004	10-03-2014 11:45AM
0.006	10-03-2014 11:15AM
0.003	10-03-2014 10:45AM
0.005	10-03-2014 10:15AM
0.006	10-03-2014 10:00AM

Figure 8: Sample reads

Results for Scalar KW

Measurements

Measurement Date/Time	Measurement
	KW
10-12-2014 01:00PM	-0.051000
09-22-2014 09:30AM	0.001000
09-15-2014 09:45AM	0.000000
09-09-2014 09:45AM	0.053000
09-02-2014 04:30PM	0.000000

Figure 9: Scalar KW results

2) 2.16.840.1.114416.1.24.1498892
Badge: 73FED00009-01498892 - Itron SN: NXF312197984

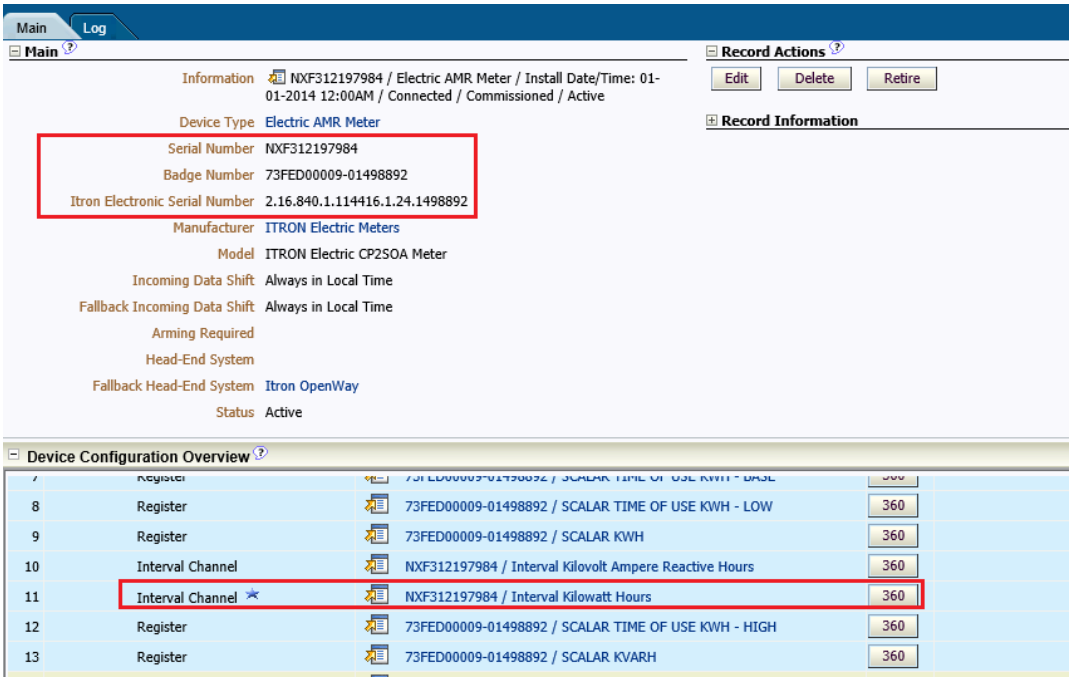


Figure 10: Device Configuration Overview

Attached sample data showing the reads for 9/30 & 10/3 with excel export

Measuren	Measurement Date/Time
KWH	
0.006	10-03-2014 01:15PM
0.005	10-03-2014 12:45PM
0.006	10-03-2014 12:30PM
0.005	10-03-2014 12:00PM
0.01	10-03-2014 11:30AM
0.011	10-03-2014 11:15AM
0.013	10-03-2014 10:45AM
0.013	10-03-2014 10:30AM
0.005	10-03-2014 10:15AM
0.005	10-03-2014 10:00AM
0.005	10-03-2014 09:45AM
0.005	10-03-2014 09:30AM
0.004	10-03-2014 09:15AM
0.005	10-03-2014 09:00AM
0.005	10-03-2014 08:45AM
0.005	10-03-2014 08:00AM

Figure 11: Sample read 9/30 & 10/3

Results for Scalar KW

Measurement Date/Time	Measurement
	KW
10-11-2014 09:30AM	0.337000
09-08-2014 10:45AM	0.000000

Figure 12: Scalar KW results 10/11/14

3. **Collect load profile and register data by issuing on-demand read, for each GROUP separately, at least once during Acceptance Test.**

   Action: 4 EV meters were selected for this test and included as part of the Acceptance Test Group
   1) 2.16.840.1.114416.1.24.1498842
      Badge: 7FED00009-01498842
   2) 2.16.840.1.114416.1.24.1498892
      Badge: 73FED00009-01498892

   Acceptance Criteria: Metering data to be collected successfully from at least 95% of tested meters. A 'read' is considered 'successful' when all load profile data, register data, and events/alarms are collected successfully
   Date: 10/3/2014
   Result: Passed, based on the following outcomes

4 EV Meters that were part of Acceptance Test

1) 2.16.840.1.114416.1.24.1498842
   Badge: 7FED00009-01498842 Itron SN: NXF312197831

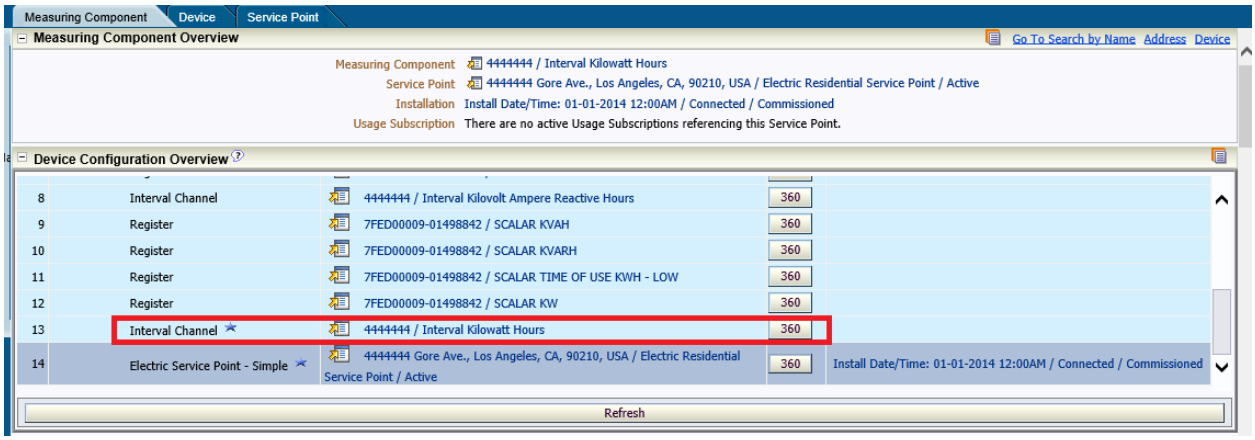


Figure 13: Device Configuration

Attached sample data showing the reads with excel export

Measurement	Measurement Date/Time
KWH	
0.001	10-03-2014 01:15PM
0.003	10-03-2014 01:00PM
0.003	10-03-2014 12:45PM
0.005	10-03-2014 12:30PM
0.005	10-03-2014 12:15PM
0.002	10-03-2014 12:00PM
0.004	10-03-2014 11:45AM
0.006	10-03-2014 11:15AM
0.003	10-03-2014 10:45AM
0.005	10-03-2014 10:15AM
0.006	10-03-2014 10:00AM

Figure 14: Sample data 10-3-14

Results for Scalar KW

Measurements

Measurement Date/Time	Measurement
	KW
10-12-2014 01:00PM	-0.051000
09-22-2014 09:30AM	0.001000
09-15-2014 09:45AM	0.000000
09-09-2014 09:45AM	0.053000
09-02-2014 04:30PM	0.000000

Figure 15: Scalar KW Sept. – Oct. 2014

2) 2.16.840.1.114416.1.24.1498892
Badge: 73FED00009-01498892 - Itron SN: NXF312197984

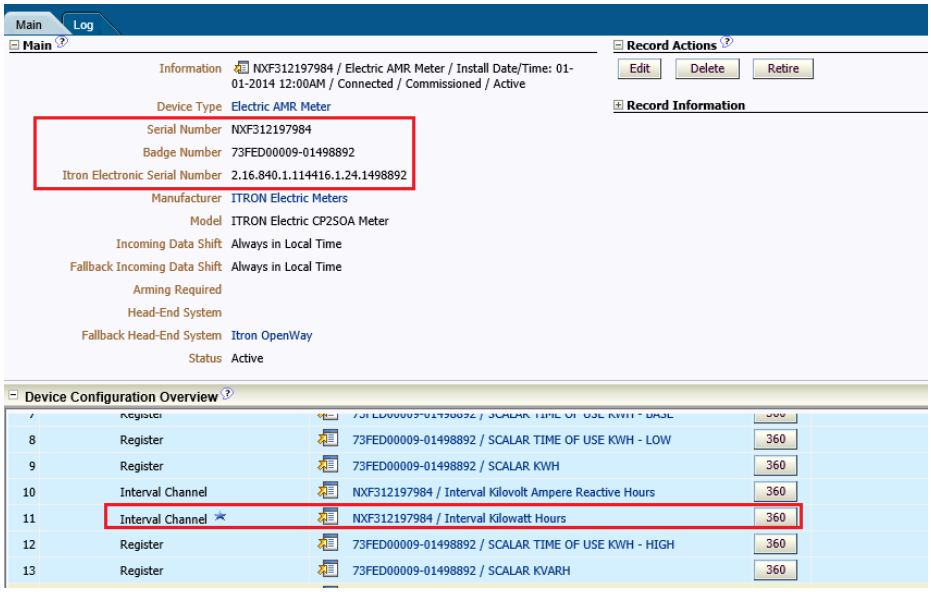


Figure 16: Main view

Attached sample data showing the reads for 9/30 & 10/3 with excel export

Measuren	Measurement Date/Time
KWH	
0.006	10-03-2014 01:15PM
0.005	10-03-2014 12:45PM
0.006	10-03-2014 12:30PM
0.005	10-03-2014 12:00PM
0.01	10-03-2014 11:30AM
0.011	10-03-2014 11:15AM
0.013	10-03-2014 10:45AM
0.013	10-03-2014 10:30AM
0.005	10-03-2014 10:15AM
0.005	10-03-2014 10:00AM
0.005	10-03-2014 09:45AM
0.005	10-03-2014 09:30AM
0.004	10-03-2014 09:15AM
0.005	10-03-2014 09:00AM
0.005	10-03-2014 08:45AM
0.005	10-03-2014 08:00AM

Figure 17: Read Rates 10/3/2014

Results for Scalar KW

Measurement Date/Time	Measurement
	KW
10-11-2014 09:30AM	0.337000
09-08-2014 10:45AM	0.000000

Figure 18: Results 9/2014 – 10/ 2014

Part 2: Metering Events and Exceptions

Events and Exceptions indicate the “abnormal” or “unwanted” condition from the meter or the service, reported by the meter.

4. **Conditions for a few ‘events’ shall be created to ensure appropriate alarms are being generated.**

   Action: Following meter was selected: 7AED00009-01499052
   ESN 2.16.840.1.114416.1.24.1499052

Action: Events/exceptions are appropriately generated by the meter and collected successfully

Date: 10/15/2014, 10/16/2014

Result: Passed, based on following outcomes

Test Results for Generating Events/Exceptions for an EV Meter as part of the Itron Acceptance Testing

Test Meter: 7AED00009-01499052

ESN - 2.16.840.1.114416.1.24.1499052

Date & Time: 10/16/2014 @ 3:46 pm

1) Trigger a Power Off on the meter by turning off the switch and confirmed that the meter was completedly turned off
2) Waited 45 seconds and then Power the meter back on and confirmed the meter came back on
3) Confirmed in CE that the meter generated the needed event and exceptions

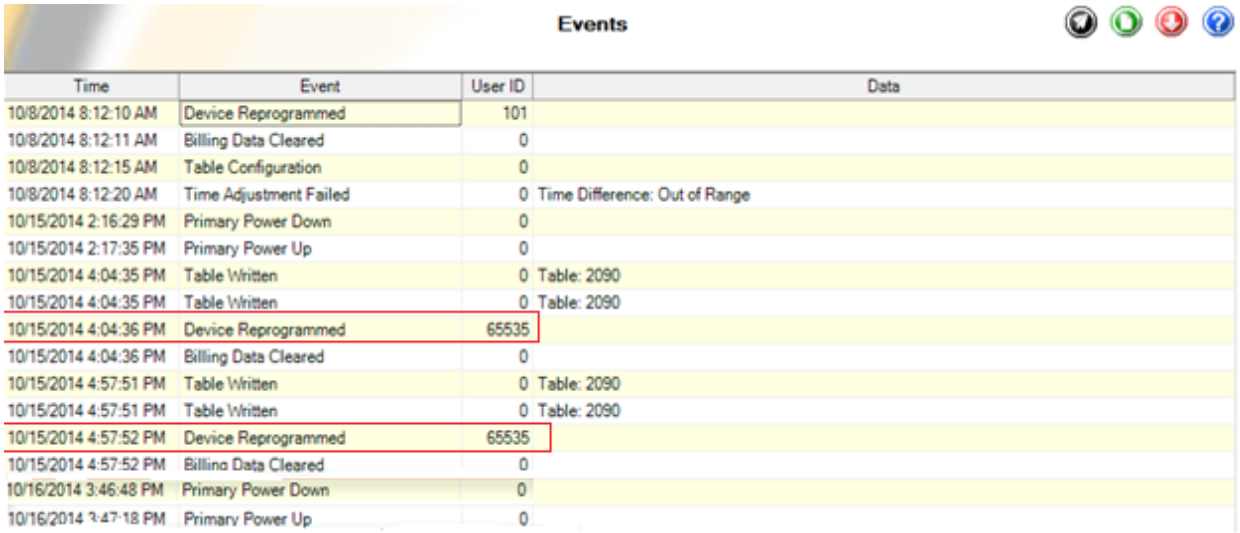
Events

Time	Event	User ID	Data
10/8/2014 8:12:10 AM	Device Reprogrammed	101	
10/8/2014 8:12:11 AM	Billing Data Cleared	0	
10/8/2014 8:12:15 AM	Table Configuration	0	
10/8/2014 8:12:20 AM	Time Adjustment Failed	0	Time Difference: Out of Range
10/15/2014 2:16:29 PM	Primary Power Down	0	
10/15/2014 2:17:35 PM	Primary Power Up	0	
10/15/2014 4:04:35 PM	Table Written	0	Table: 2090
10/15/2014 4:04:35 PM	Table Written	0	Table: 2090
10/15/2014 4:04:36 PM	Device Reprogrammed	65535	
10/15/2014 4:04:36 PM	Billing Data Cleared	0	
10/15/2014 4:57:51 PM	Table Written	0	Table: 2090
10/15/2014 4:57:51 PM	Table Written	0	Table: 2090
10/15/2014 4:57:52 PM	Device Reprogrammed	65535	
10/15/2014 4:57:52 PM	Billing Data Cleared	0	
10/16/2014 3:46:48 PM	Primary Power Down	0	
10/16/2014 3:47:18 PM	Primary Power Up	0	

Figure 19: Power events

4) Also, on 10/15, we completed a meter reprogram of the same meter as part of another Itron Acceptance Test
    - Meter Reprogram from Config 64 kWh TOU Single ICS to Config 60 kWh Only Single ICS (Date: 10/15 @ 4:04 pm)
    - Reprogram meter back to its original Configuration Group (50 back to 60) (Date: 10/15 @ 4:57 pm)

Confirmed that the Meter produced the expected event related to these meters



Events

Time	Event	User ID	Data
10/8/2014 8:12:10 AM	Device Reprogrammed	101	
10/8/2014 8:12:11 AM	Billing Data Cleared	0	
10/8/2014 8:12:15 AM	Table Configuration	0	
10/8/2014 8:12:20 AM	Time Adjustment Failed	0	Time Difference: Out of Range
10/15/2014 2:16:29 PM	Primary Power Down	0	
10/15/2014 2:17:35 PM	Primary Power Up	0	
10/15/2014 4:04:35 PM	Table Written	0	Table: 2090
10/15/2014 4:04:35 PM	Table Written	0	Table: 2090
10/15/2014 4:04:36 PM	Device Reprogrammed	65535	
10/15/2014 4:04:36 PM	Billing Data Cleared	0	
10/15/2014 4:57:51 PM	Table Written	0	Table: 2090
10/15/2014 4:57:51 PM	Table Written	0	Table: 2090
10/15/2014 4:57:52 PM	Device Reprogrammed	65535	
10/15/2014 4:57:52 PM	Billing Data Cleared	0	
10/16/2014 3:46:48 PM	Primary Power Down	0	
10/16/2014 3:47:18 PM	Primary Power Up	0	

Figure 20: Re-programmed

Note: We could not capture these events in MDM, PI-Historian or K-Grid because these are the new EV meters and they have not been configured in these respective systems. As such, the only way to validate is to utilize the data results from the CE.

Part 3: Metering Configuration Program

Configuration Programs determine the functaion of the meters in terms of the type of data to be measured and reported by the meter as well as the displays to be shown.

5. **Prepare configuration programs for each GROUP, other than the configuration programs that meters are programmed with, and re-program every GROUP over-the-air at least once during Acceptance Test. Both communication methods (Cellular, RF). Meters will be read afterward to ensure re-programming took place successfully**

   Action: Following meter was selected 7AED00009-01499052
   ESN 2.16.840.1.114416.1.24.1499052

   Acceptance Criteria: Remote meter programming to be successfully performed on tested meters.

   Date: 10/15/2014

   Result: Passed, based on following outcomes

10/15/2014 @ 2-4:30 pm Conducted Two Tests

1) Meter Reprogram from Config_64_kwh_ tou_single_ ICS_ev to Config_60 _single_ICS_Solar
2) Reprogram meter back from Config_60 _single_ICS_Solar to its original Config_64_kwh_ tou_single_ ICS_ev

Test using meter with batch number: 7AED00009-01499052 with ESN 2.16.840.1.114416.1.24.1499052

1) Confirmed Meter is in Config_64_kwh_ tou_single_ ICS_ev and displays 01, 02, 04, 10, 16 and 39



Figure 21: Meter Configuration

Confirmed in CE that ESN for this meter matches and that it is currenctly in Config_64_kwh_ tou_single_ ICS_ev

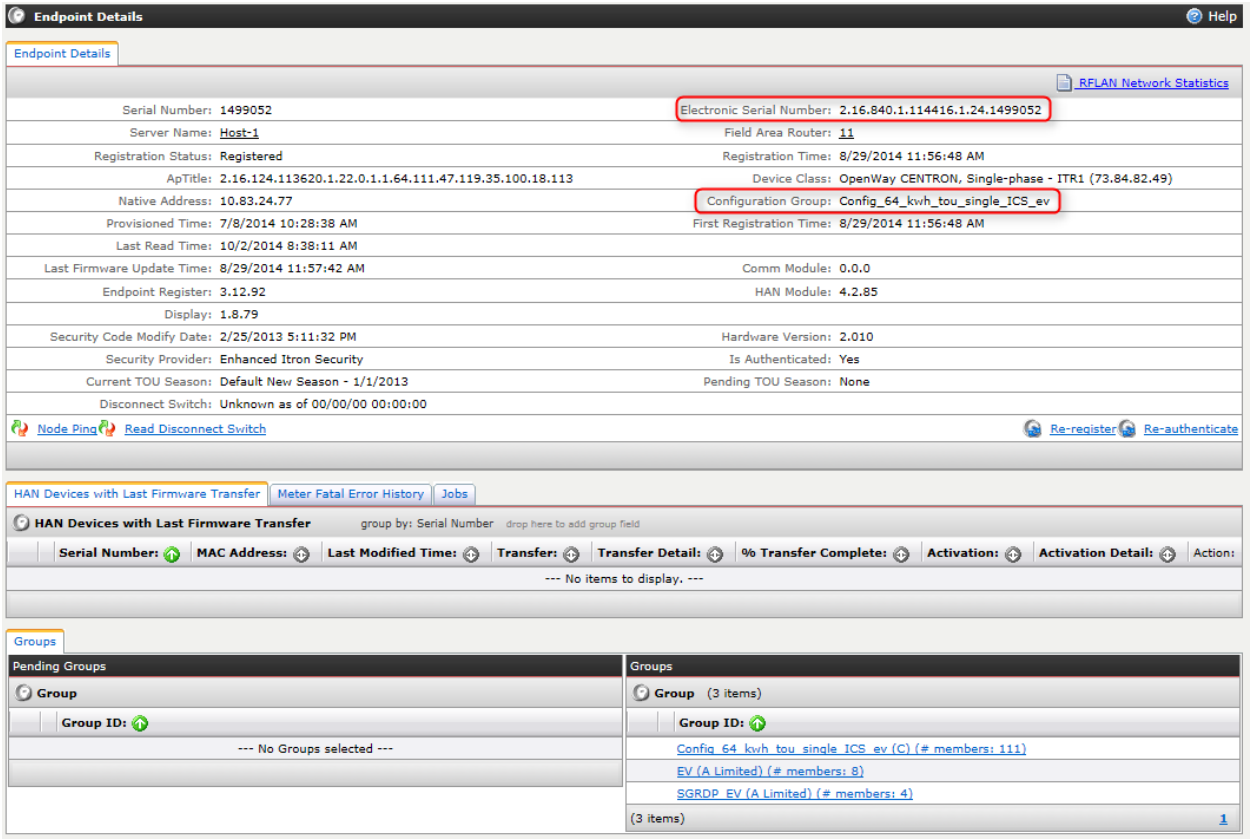


Figure 22: Meter Configuration in CE

Specs for Config_60 _single_ICS_Solar confirming it has displayed 01, 02, 04, 10, 16 and 39

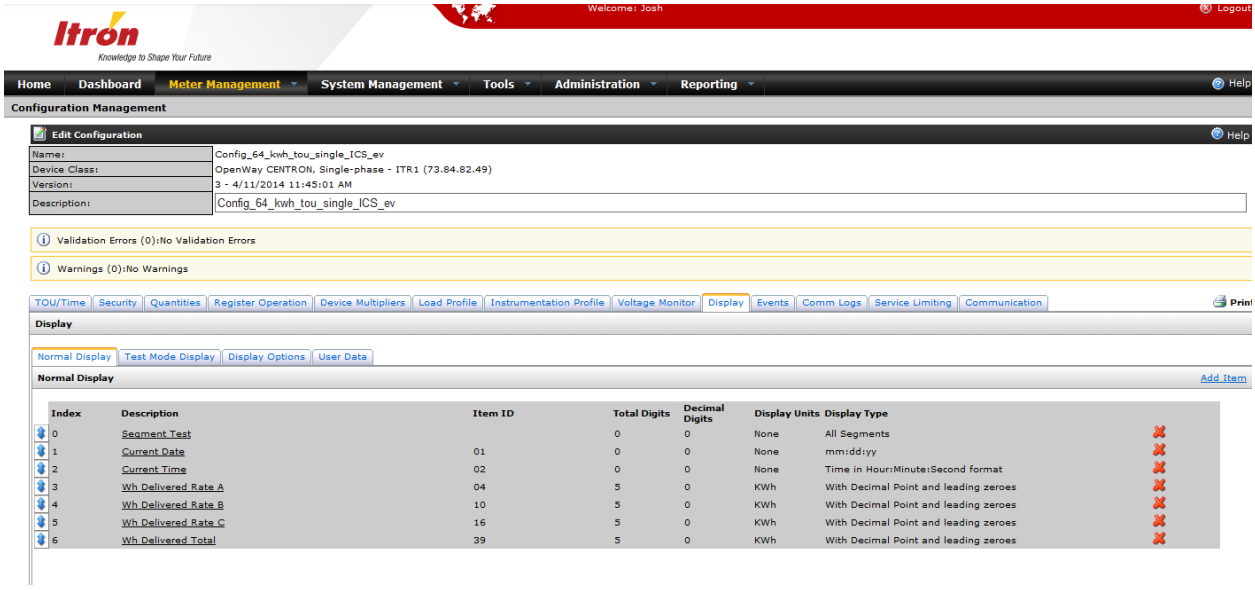


Figure 23: Specs for Config_60

2) Before moving configuration group, completed an interrogation read through the CE to ensure that meter is communicating

Register Data

Register Name:	Value:	Time of Occurrence:	Source:
ccum W d	0	10/15/2014 2:44:00 PM	Current
ccum W d Rate A	0	10/15/2014 2:44:00 PM	Current
ccum W d Rate B	0	10/15/2014 2:44:00 PM	Current
ccum W d Rate C	0	10/15/2014 2:44:00 PM	Current
cum W d	0	10/15/2014 2:44:00 PM	Current
cum W d Rate A	0	10/15/2014 2:44:00 PM	Current
cum W d Rate B	0	10/15/2014 2:44:00 PM	Current
cum W d Rate C	0	10/15/2014 2:44:00 PM	Current
ins V(a)	120.8	10/15/2014 2:44:00 PM	Present
max W d	0	10/8/2014 8:12:00 AM	Current
max W d Rate A	0	10/8/2014 8:12:00 AM	Current
max W d Rate B	0	10/8/2014 8:12:00 AM	Current
max W d Rate C	0	10/8/2014 8:12:00 AM	Current
Number of Demand Resets	0	10/15/2014 2:44:00 PM	Present
Number of Inversion Tampers	0	10/15/2014 2:44:00 PM	Present
Number of minutes on battery carryover	96674	10/15/2014 2:44:00 PM	Present
Number of Power Outages	3	10/15/2014 2:44:00 PM	Present
Number of Removal Tampers	0	10/15/2014 2:44:00 PM	Present
Number of times programmed	4	10/15/2014 2:44:00 PM	Present
VAh d	0	10/15/2014 2:44:00 PM	Current
VAh d Rate A	0	10/15/2014 2:44:00 PM	Current
VAh d Rate B	0	10/15/2014 2:44:00 PM	Current
VAh d Rate C	0	10/15/2014 2:44:00 PM	Current
Wh d	0	10/15/2014 2:44:00 PM	Current
Wh d Rate A	0	10/15/2014 2:44:00 PM	Current
Wh d Rate B	0	10/15/2014 2:44:00 PM	Current
Wh d Rate C	0	10/15/2014 2:44:00 PM	Current

History Log

Event Date/Time:	Event:	Event Parameters:
10/15/2014 2:16:29 PM	Primary Power Down	
10/15/2014 2:17:35 PM	Primary Power Up	
10/15/2014 2:17:35 PM	HAN Meter Network Change	Meter Network Status = Network Up, Network Change Reason = Network Restart

Figure 24: Interrogation read

3) Move meter from Config 64 kWH TOU single ICS to Config_60 _single_ICS_Solar

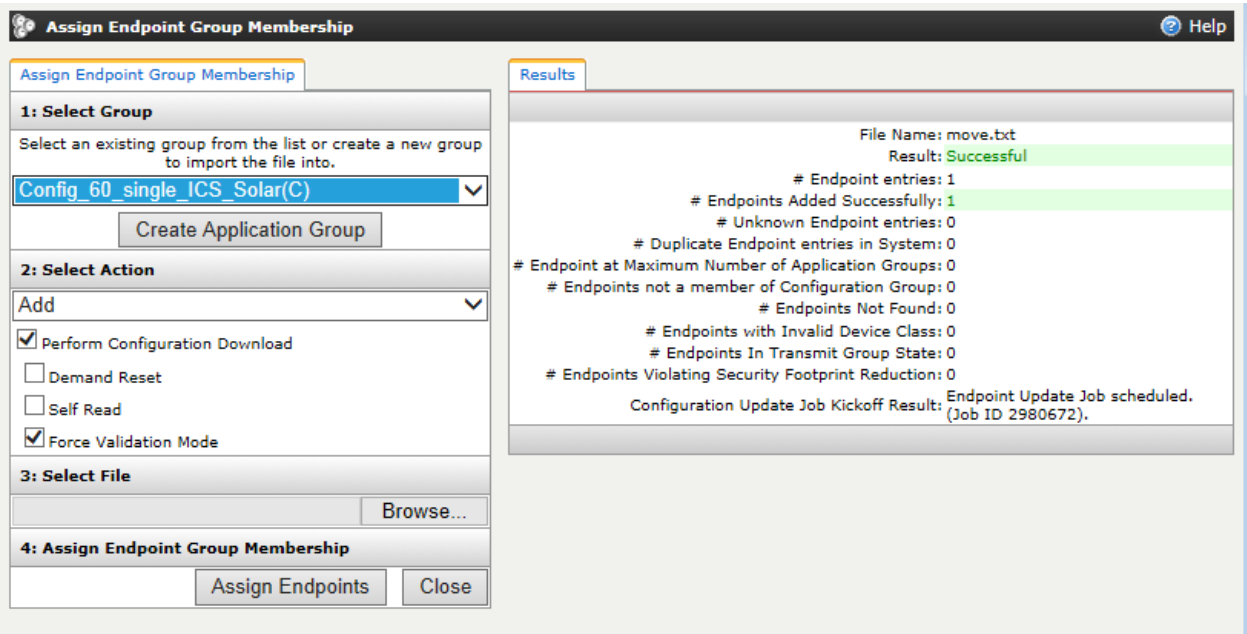


Figure 25: Assign Endpoint Group Membership

4) Request a meter interrogation of the meter through CE and confirmed that the meter moved to Config_60 _single_ICS_Solar

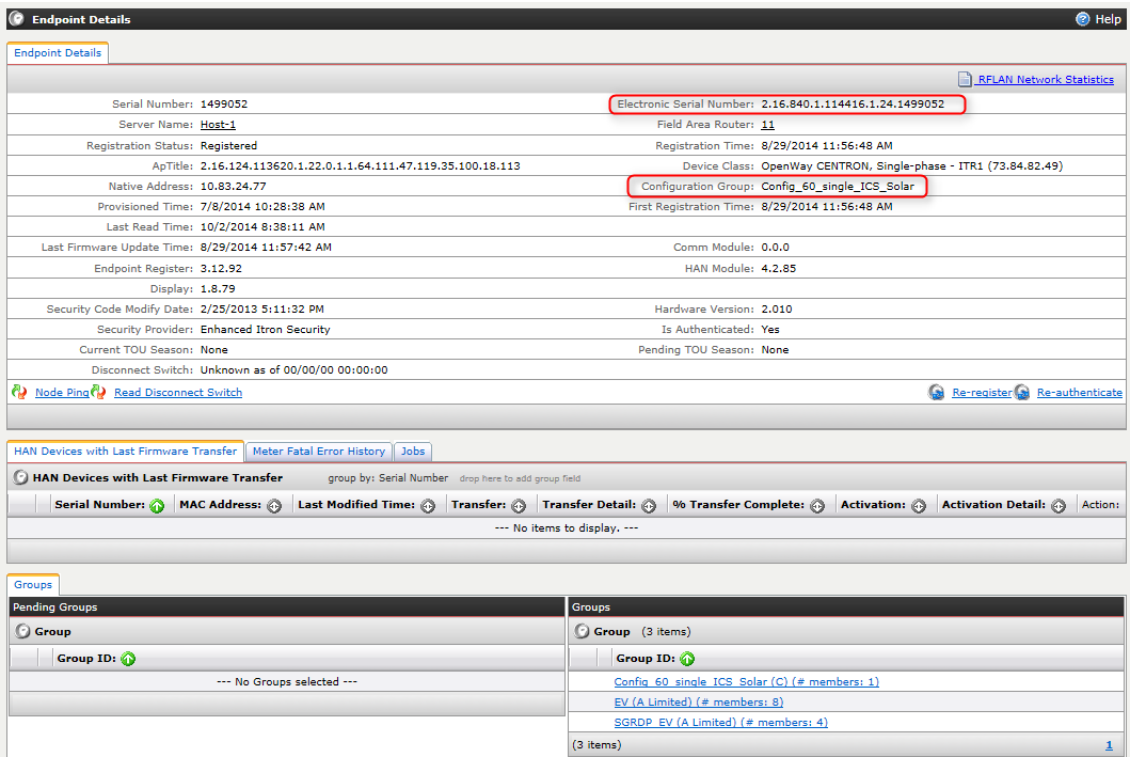


Figure 26: Endpoint Details

5) Confirmed specs for Config_60 _single_ICS_Solar confirm that it has both Display 39 only

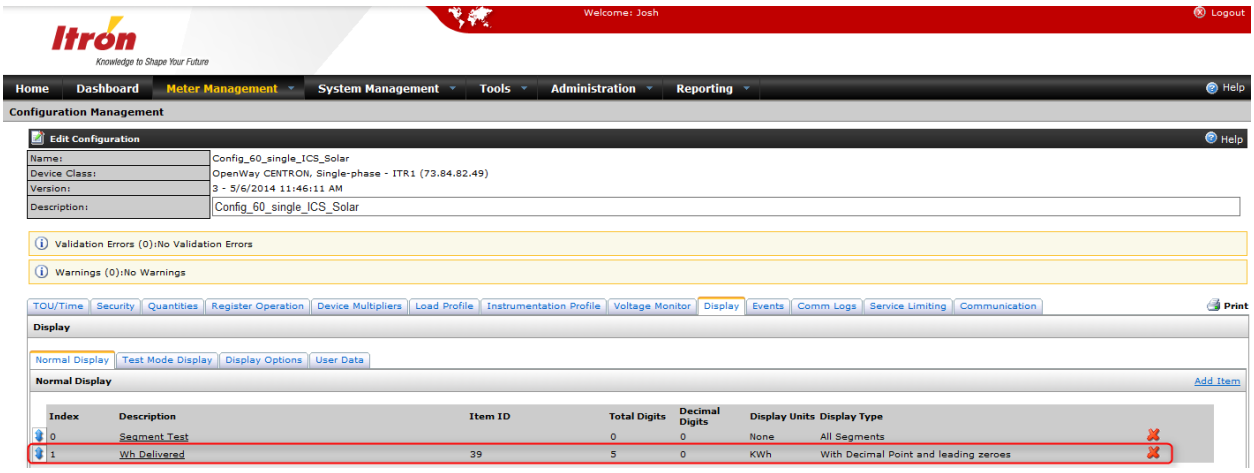


Figure 27: View Configuration

6) Confirmed that on display of the meter, it is showing only Display 39 (kWh) after the meter reprogrammed
First validated display 39 – see image attached



Figure 28: Display of meter

7) Re-programmed the meter back from Config_60 _single_ICS_Solar back to Config_64_kwh_ tou_single_ ICS_ev

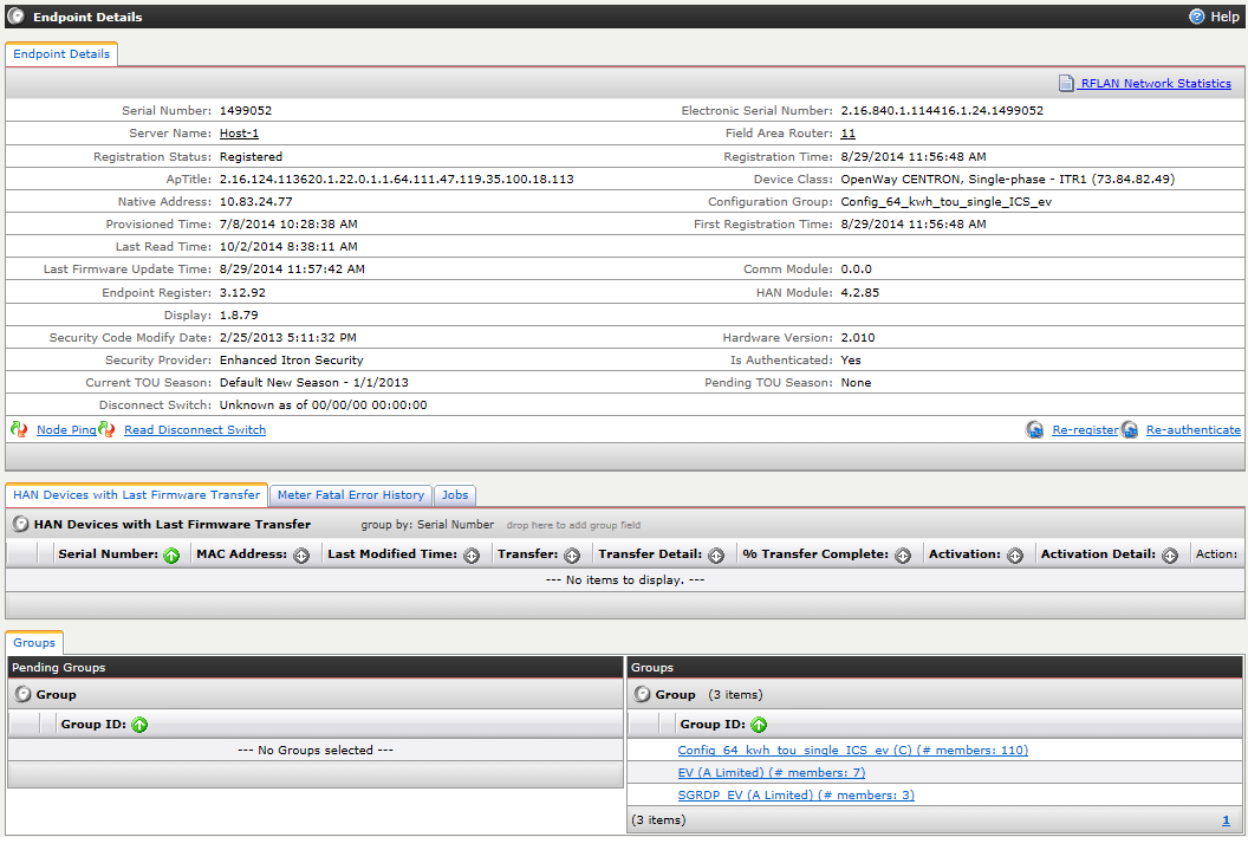


Figure 29: Re-programmed the meter back from Config_60 _single_ICS_Solar

8) Completed an interactive read from CE to confirm registers in Config_60_kwh_only.

Serial Number	1499052
Electronic Serial Number	2.16.840.1.114416.1.24.1499052
Interactive Read Time	10/15/2014 5:00:20 PM
Time Zone	(GMT-08:00) Pacific Time (US & Canada); Tijuana
Requested Time Span	10/15/2014 4:00:20 PM - 10/15/2014 5:00:20 PM
Job Status	Successful
Job Duration	00:00:53

Register Data

Register Name:	Value:	Time of Occurrence:	Source:
ccum W d	0	10/15/2014 5:00:29 PM	Current
ccum W d Rate A	0	10/15/2014 5:00:29 PM	Current
ccum W d Rate B	0	10/15/2014 5:00:29 PM	Current
ccum W d Rate C	0	10/15/2014 5:00:29 PM	Current
cum W d	0	10/15/2014 5:00:29 PM	Current
cum W d Rate A	0	10/15/2014 5:00:29 PM	Current
cum W d Rate B	0	10/15/2014 5:00:29 PM	Current
cum W d Rate C	0	10/15/2014 5:00:29 PM	Current
ins V(a)	121.9	10/15/2014 5:00:29 PM	Present
max W d	0	10/15/2014 4:57:00 PM	Current
max W d Rate A	0	10/15/2014 4:57:00 PM	Current
max W d Rate B	0	10/15/2014 4:57:00 PM	Current
max W d Rate C	0	10/15/2014 4:57:00 PM	Current
Number of Demand Resets	0	10/15/2014 5:00:29 PM	Present
Number of Inversion Tampers	0	10/15/2014 5:00:29 PM	Present
Number of minutes on battery carryover	96674	10/15/2014 5:00:29 PM	Present
Number of Power Outages	3	10/15/2014 5:00:29 PM	Present
Number of Removal Tampers	0	10/15/2014 5:00:29 PM	Present
Number of times programmed	6	10/15/2014 5:00:29 PM	Present
VAh d	0	10/15/2014 5:00:29 PM	Current
VAh d Rate A	0	10/15/2014 5:00:29 PM	Current
VAh d Rate B	0	10/15/2014 5:00:29 PM	Current
VAh d Rate C	0	10/15/2014 5:00:29 PM	Current
Wh d	0	10/15/2014 5:00:29 PM	Current
Wh d Rate A	0	10/15/2014 5:00:29 PM	Current
Wh d Rate B	0	10/15/2014 5:00:29 PM	Current
Wh d Rate C	0	10/15/2014 5:00:29 PM	Current

Figure 30: Interactive read - confirm registration

9) Check meter and confirm that meter is showing all displays of Config_64_kwh_ tou_single_ ICS_ev (01, 02, 04, 10, 16 and 39)

   See image attached.



Figure 31: Displays of Configuration

6. **Re-program all the programmed meters back to their original configuration programs over-the-air. Meters shall be read afterward to ensure re-programming took place successfully.**

   Action: Following meter was selected 7AED00009-01499052
   ESN 2.16.840.1.114416.1.24.1499052

   Acceptance Criteria: Remote meter programming to be successfully performed on at tested meters.

   Date: 10/15/2014

   Result: Passed, based on the following outcomes

- Meter Reprogram from Config_64_kwh_ tou_single_ ICS_ev to Config_60 _single_ICS_Solar (Date & Time: 10/15/2014 @ 4:04 pm)

- Reprogram meter back from Config_60 _single_ICS_Solar to its original Config_64_kwh_ tou_single_ ICS_ev (Date & Time: 10/15/2014 @ 4:57 pm)

Test using meter with batch number: 7AED00009-01499052 with ESN 2.16.840.1.114416.1.24.1499052

Confirmed Meter is in Config_64_kwh_ tou_single_ ICS_ev and showing display 01, 02, 04, 10, 16 and 39



Figure 32: Config_64_kwh_ tou_single_ ICS_ev

Confirmed in CE that ESN for this meter matches and that it is currently in Config_64_kwh_ tou_single_ ICS_ev

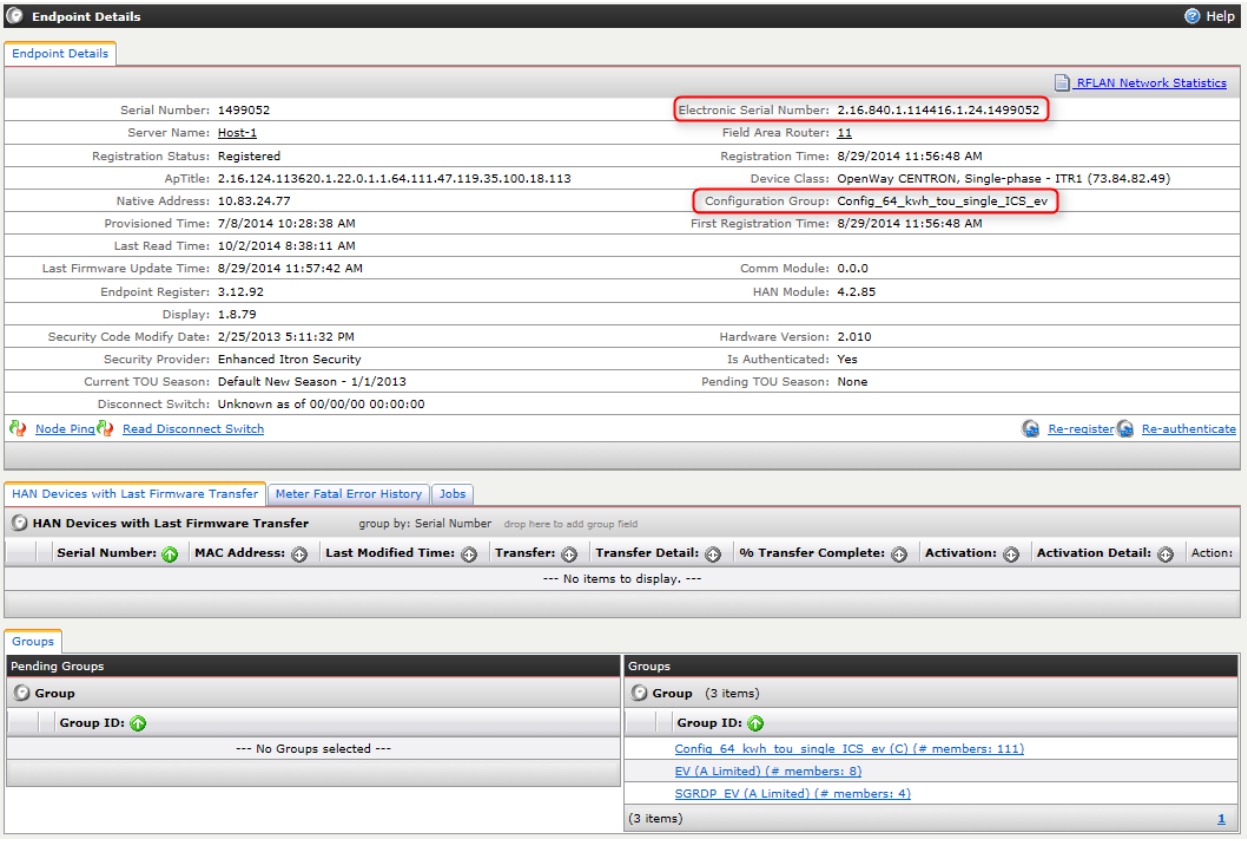


Figure 33: Confirm in CE - Config_64_kwh_ tou_single_ ICS_ev

Specs for Config_60 _single_ICS_Solar confirming it has displayed 01, 02, 04, 10, 16 and 39

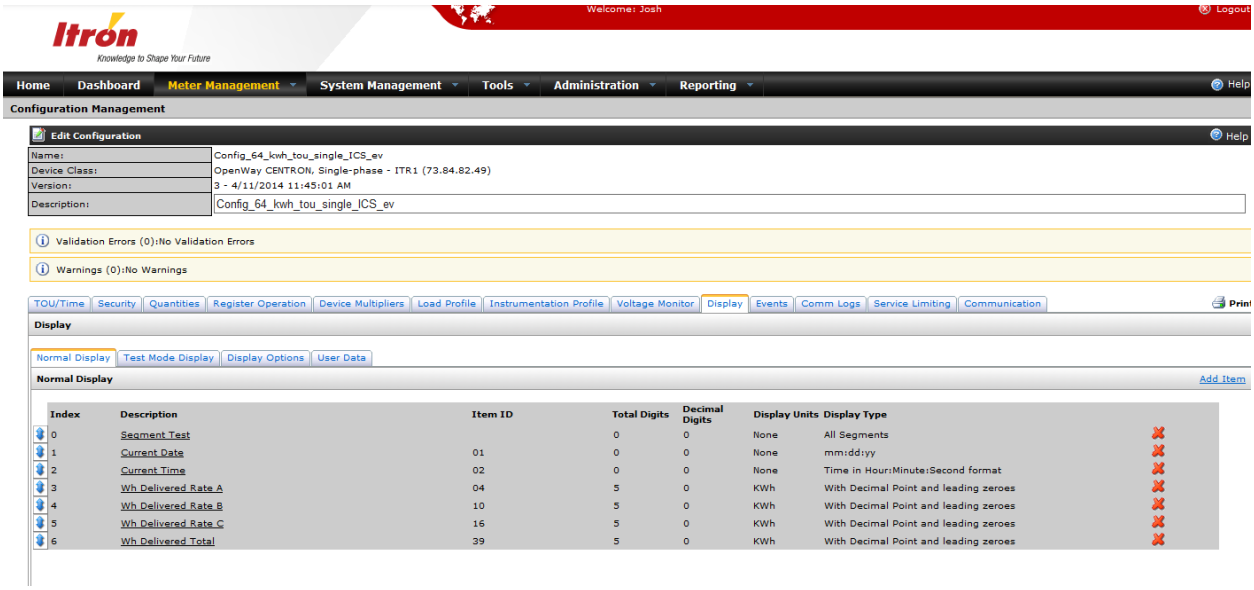


Figure 34: Specs for Config_60 _single_ICS_Solar

10) Before moving configuration group, completed an interrogation read through the CE to ensure that meter is communicating

Register Data

Register Name:	Value:	Time of Occurrence:	Source:
ccum W d	0	10/15/2014 2:44:00 PM	Current
ccum W d Rate A	0	10/15/2014 2:44:00 PM	Current
ccum W d Rate B	0	10/15/2014 2:44:00 PM	Current
ccum W d Rate C	0	10/15/2014 2:44:00 PM	Current
cum W d	0	10/15/2014 2:44:00 PM	Current
cum W d Rate A	0	10/15/2014 2:44:00 PM	Current
cum W d Rate B	0	10/15/2014 2:44:00 PM	Current
cum W d Rate C	0	10/15/2014 2:44:00 PM	Current
ins V(a)	120.8	10/15/2014 2:44:00 PM	Present
max W d	0	10/8/2014 8:12:00 AM	Current
max W d Rate A	0	10/8/2014 8:12:00 AM	Current
max W d Rate B	0	10/8/2014 8:12:00 AM	Current
max W d Rate C	0	10/8/2014 8:12:00 AM	Current
Number of Demand Resets	0	10/15/2014 2:44:00 PM	Present
Number of Inversion Tampers	0	10/15/2014 2:44:00 PM	Present
Number of minutes on battery carryover	96674	10/15/2014 2:44:00 PM	Present
Number of Power Outages	3	10/15/2014 2:44:00 PM	Present
Number of Removal Tampers	0	10/15/2014 2:44:00 PM	Present
Number of times programmed	4	10/15/2014 2:44:00 PM	Present
VAh d	0	10/15/2014 2:44:00 PM	Current
VAh d Rate A	0	10/15/2014 2:44:00 PM	Current
VAh d Rate B	0	10/15/2014 2:44:00 PM	Current
VAh d Rate C	0	10/15/2014 2:44:00 PM	Current
Wh d	0	10/15/2014 2:44:00 PM	Current
Wh d Rate A	0	10/15/2014 2:44:00 PM	Current
Wh d Rate B	0	10/15/2014 2:44:00 PM	Current
Wh d Rate C	0	10/15/2014 2:44:00 PM	Current

History Log

Event Date/Time:	Event:	Event Parameters:
10/15/2014 2:16:29 PM	Primary Power Down	
10/15/2014 2:17:35 PM	Primary Power Up	
10/15/2014 2:17:35 PM	HAN Meter Network Change	Meter Network Status = Network Up, Network Change Reason = Network Restart

Figure 35: Interrogation read - confirm communicating

11) Move meter from Config 64 kWH TOU single ICS to Config_60 _single_ICS_Solar

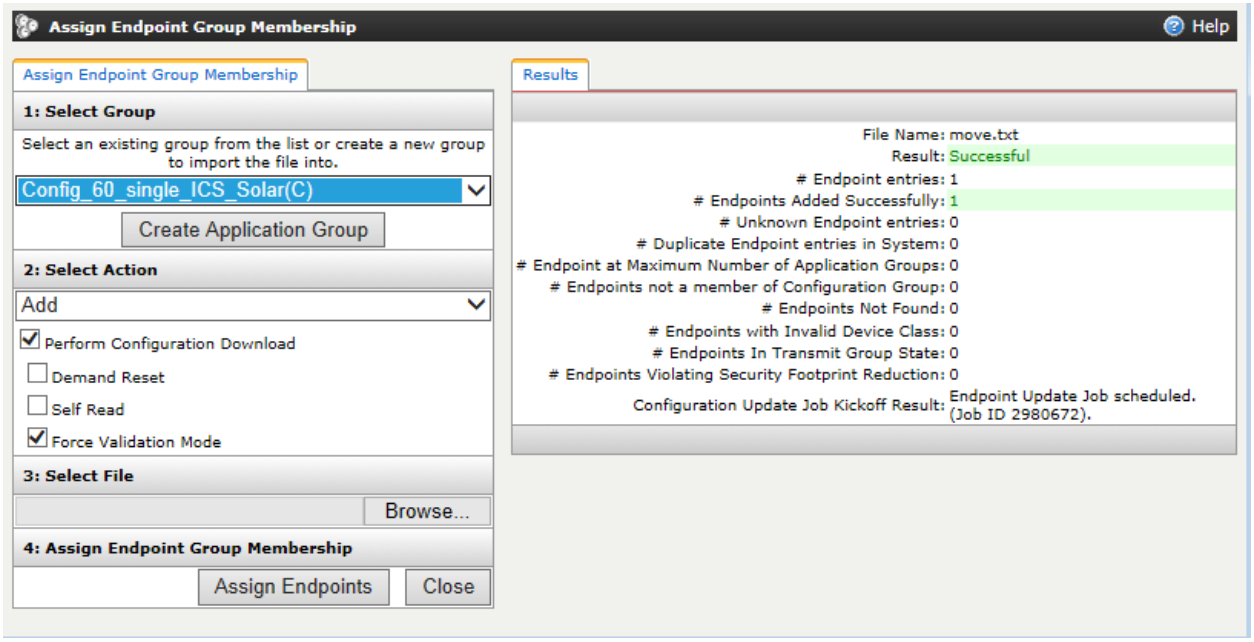


Figure 36: Config 64 kWH TOU single ICS to Config_60 _single_ICS_Solar

12) Request a meter interrogation of the meter through CE and confirmed that the meter moved to Config_60 _single_ICS_Solar

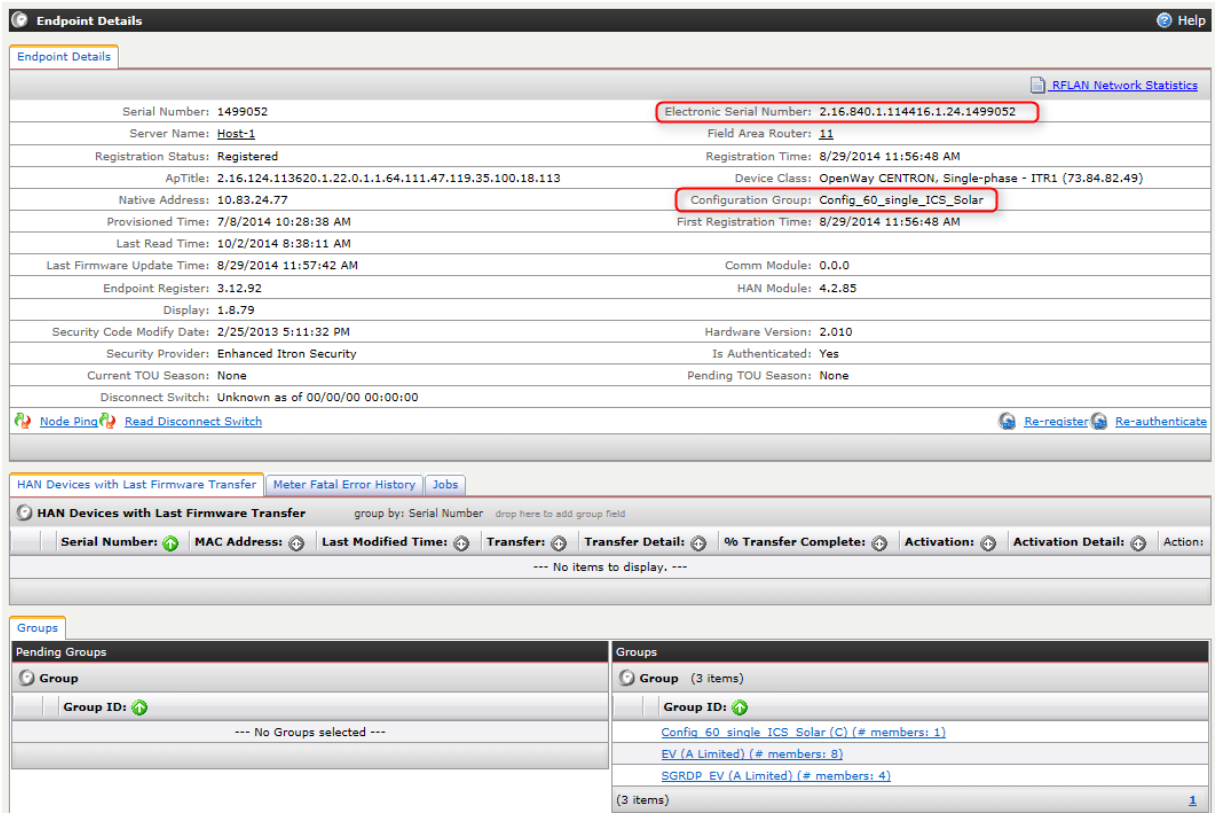


Figure 37: Confirmed that the meter moved to Config_60 _single_ICS_Solar

13) Confirmed specs for Config_60 _single_ICS_Solar confirm that it has both Display 39 only

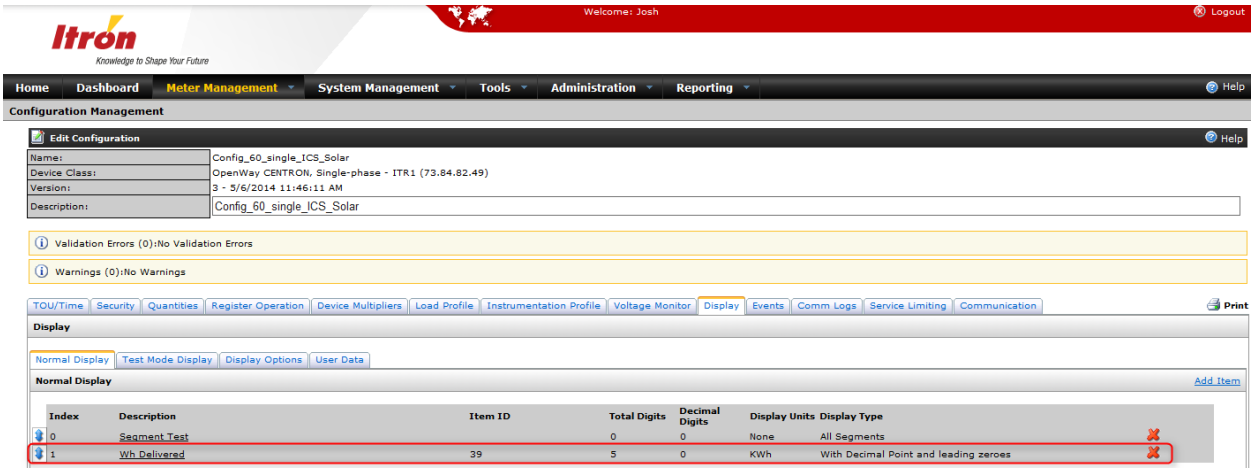


Figure 38: Confirmed specs for Config_60 _single_ICS_Solar

14) Confirmed that on display of the meter, it is showing only Display 39 (kWh) after the meter reprogrammed
First validated display 39 – see image attached



Figure 39: Display 39

15) Re-programmed the meter back from Config_60 _single_ICS_Solar back to Config_64_kwh_ tou_single_ ICS_ev

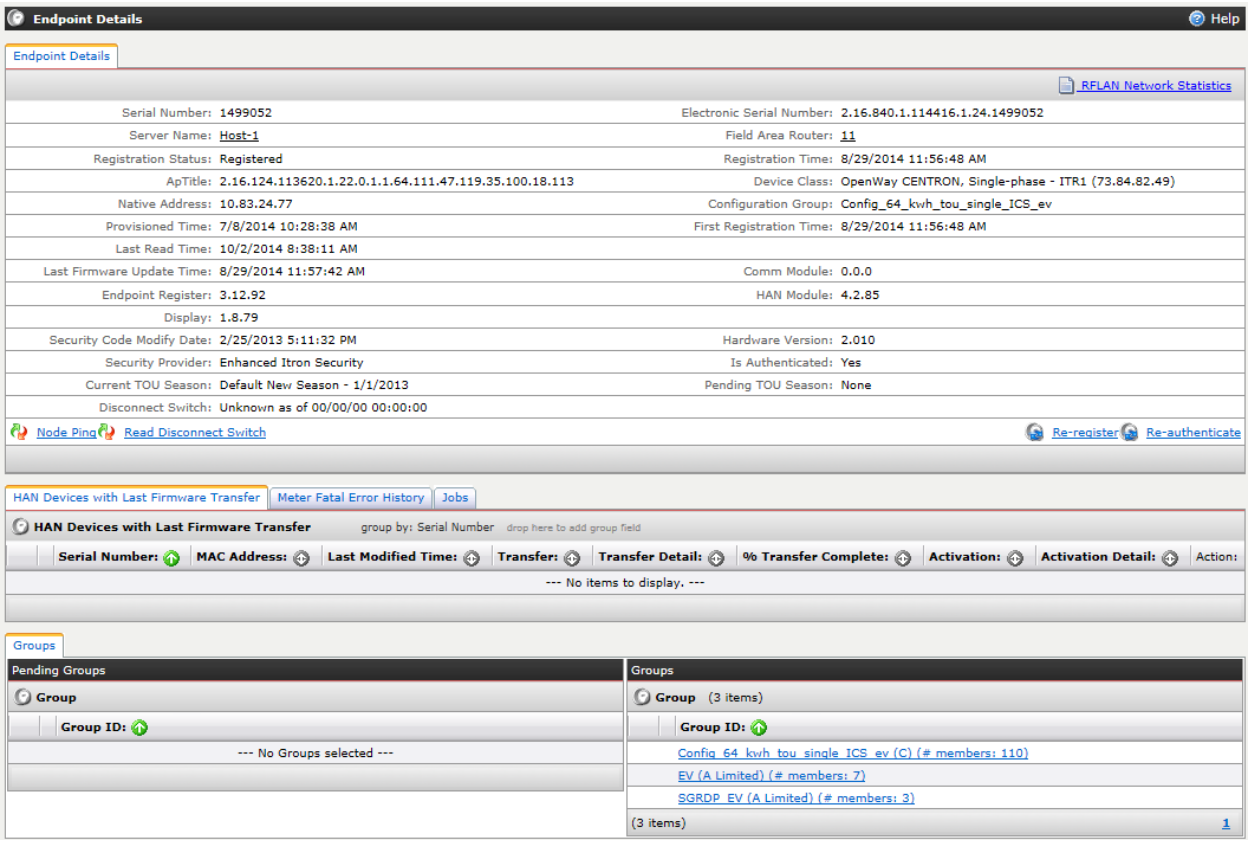


Figure 40 :Config_60 _single_ICS_Solar back to Config_64_kwh_ tou_single_ ICS_ev

16) Completed an interactive read from CE to confirm registers in Config_60_kwh_only.

Serial Number	1499052
Electronic Serial Number	2.16.840.1.114416.1.24.1499052
Interactive Read Time	10/15/2014 5:00:20 PM
Time Zone	(GMT-08:00) Pacific Time (US & Canada); Tijuana
Requested Time Span	10/15/2014 4:00:20 PM - 10/15/2014 5:00:20 PM
Job Status	Successful
Job Duration	00:00:53

Register Data

Register Name:	Value:	Time of Occurrence:	Source:
ccum W d	0	10/15/2014 5:00:29 PM	Current
ccum W d Rate A	0	10/15/2014 5:00:29 PM	Current
ccum W d Rate B	0	10/15/2014 5:00:29 PM	Current
ccum W d Rate C	0	10/15/2014 5:00:29 PM	Current
cum W d	0	10/15/2014 5:00:29 PM	Current
cum W d Rate A	0	10/15/2014 5:00:29 PM	Current
cum W d Rate B	0	10/15/2014 5:00:29 PM	Current
cum W d Rate C	0	10/15/2014 5:00:29 PM	Current
ins V(a)	121.9	10/15/2014 5:00:29 PM	Present
max W d	0	10/15/2014 4:57:00 PM	Current
max W d Rate A	0	10/15/2014 4:57:00 PM	Current
max W d Rate B	0	10/15/2014 4:57:00 PM	Current
max W d Rate C	0	10/15/2014 4:57:00 PM	Current
Number of Demand Resets	0	10/15/2014 5:00:29 PM	Present
Number of Inversion Tampers	0	10/15/2014 5:00:29 PM	Present
Number of minutes on battery carryover	96674	10/15/2014 5:00:29 PM	Present
Number of Power Outages	3	10/15/2014 5:00:29 PM	Present
Number of Removal Tampers	0	10/15/2014 5:00:29 PM	Present
Number of times programmed	6	10/15/2014 5:00:29 PM	Present
VAh d	0	10/15/2014 5:00:29 PM	Current
VAh d Rate A	0	10/15/2014 5:00:29 PM	Current
VAh d Rate B	0	10/15/2014 5:00:29 PM	Current
VAh d Rate C	0	10/15/2014 5:00:29 PM	Current
Wh d	0	10/15/2014 5:00:29 PM	Current
Wh d Rate A	0	10/15/2014 5:00:29 PM	Current
Wh d Rate B	0	10/15/2014 5:00:29 PM	Current
Wh d Rate C	0	10/15/2014 5:00:29 PM	Current

Figure 41: Confirm registers in Config_60_kwh

17) Check meter and confirm that meter is showing all display of Config_64_kwh_ tou_single_ ICS_ev (01, 02, 04, 10, 16 and 39)

See image attached.



Figure 42: Meter is showing all display of Config_64_kwh_ tou_single

Part 4: Remote Connect and Disconnect

The smart meters' capability for remote connect and remote disconnect provides the utilities with the ability to perform the service connect and service disconnect from a remote control center in a safe and secure way. An everyday case for these functions is customer's move-out from a house and move-in to a house.

The following demos are performed on residential and Commercial &Industrial (C&I) meters:

- Residential (Form 2S, programmed with configuration programs 50 or 60) meters with both RFLAN and Direct-Connect communication shall be among the selected endpoints.
- Commercial & Industrial (Form 9S or 5S or 16S, programmed with any configuration program other than 60) with RFLAN and Direct-Connect communication shall be among the selected endpoints

7. **Select at least 2 meters at LADWP lab environment. Coordinate with LADWP, and issue Remote Disconnect command to meters at least once.**

Action: Following meters were selected:

1) UCLA Meter: 7FY00009-00133315
ESN - 2.16.840.1.114416.1.24. 133315
2) Test Meter: 7F00009-1452194
ESN - 2.16.840.1.114416.1.24.1452194

Acceptance Criteria: Remote Connect to be performed successfully.

Date: 9/9/2014 and 10/16/2014

Result: Passed, based on the following outcomes

9/9/2014: Remote Connect Testing

Tester: Thuy-An, Michael

Witnesses: Emil, Afshin, Shawn and Josh

Test using meter with batch number: 7FY00009-00133315 with ESN**2.16.840.1.114416.1.24. 133315**

Account	WR No	Premise ID	Type	Classification	Address	New Meter Prefix	New Meter Size	New Meter Number	New Meter Serial Number	Old Meter Prefix	Old Meter Size	Old Meter Number	Date Completed	FI-39 RMVD KWH READ	FQ-41 RMVD KWD READ
	1360493	2068271458	NBRAC	SG-AMI-D	3300 SAWTELLE BLUNIT: 201 LOS ANGELES	7FY	9	133315	311141043	Y	9	53489	5/14/2014	40921	

Figure 43: ESN2.16.840.1.114416.1.24. 133315



Figure 44: Meter -ESN2.16.840.1.114416.1.24. 133315

Test Steps for Remote Connect

1) Navigate to Menu, click on Main Menu, drop down to Device and click on +Device
2) Select Device Identifier Type and choose Badge number and enter in 7FY00009-00133315 and click refresh

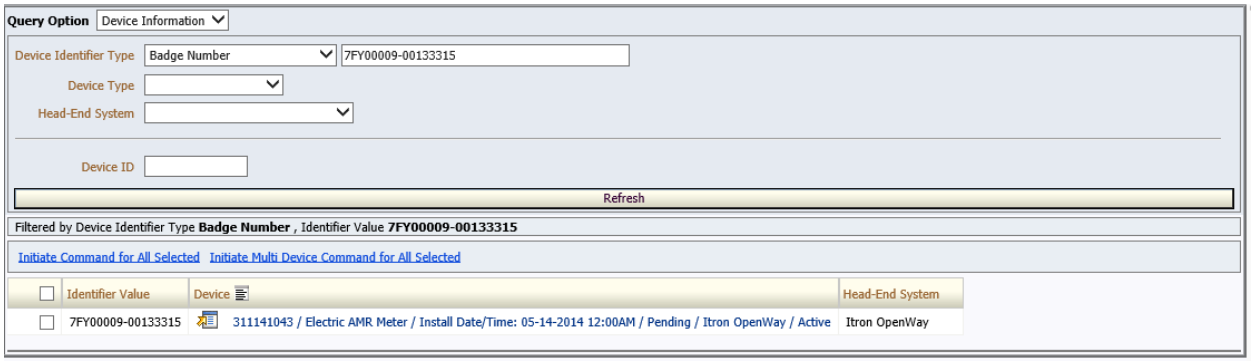


Figure 45: Menu - Remote Connect

3) Click on meter below and confirm badge number and ESN for meter

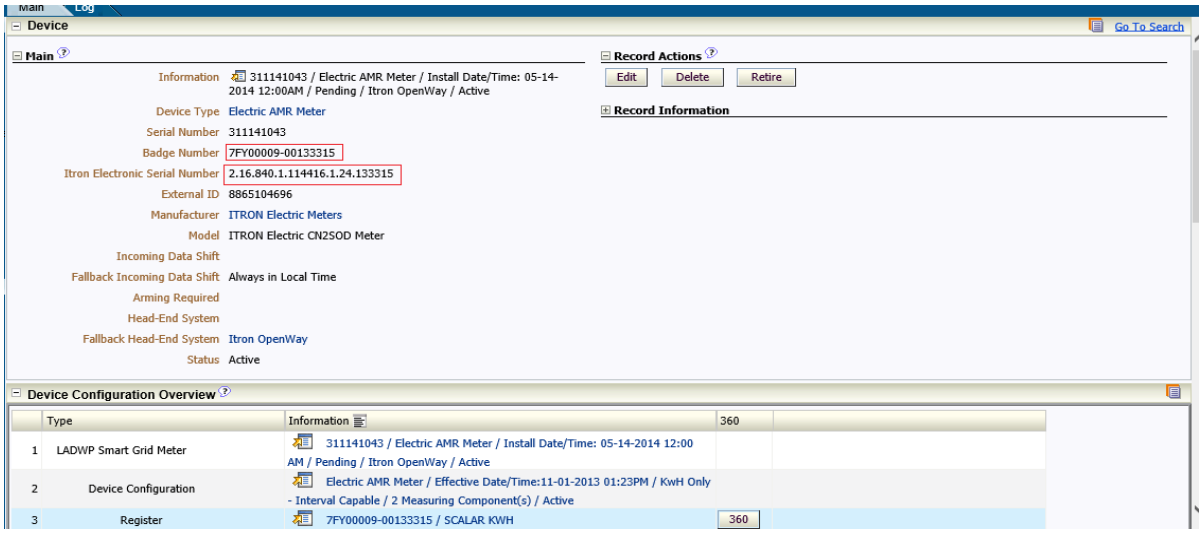


Figure 46: Confirm badge number and ESN for meter

4) Click on Service Point and confirm the meter address location matches that of 3300 SAWTELLE BL UNIT: 201

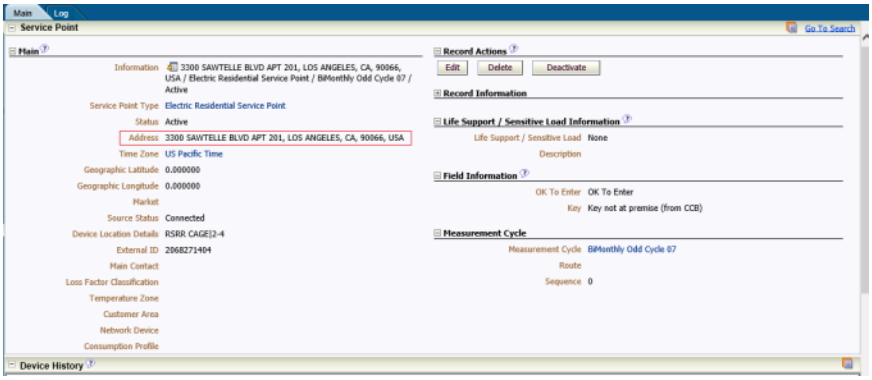


Figure 47: Confirm the meter address location

5) From Device, scroll down to Device Activities and click on “Initiate Command”, from drop down select Remote Connect, and click “ok”

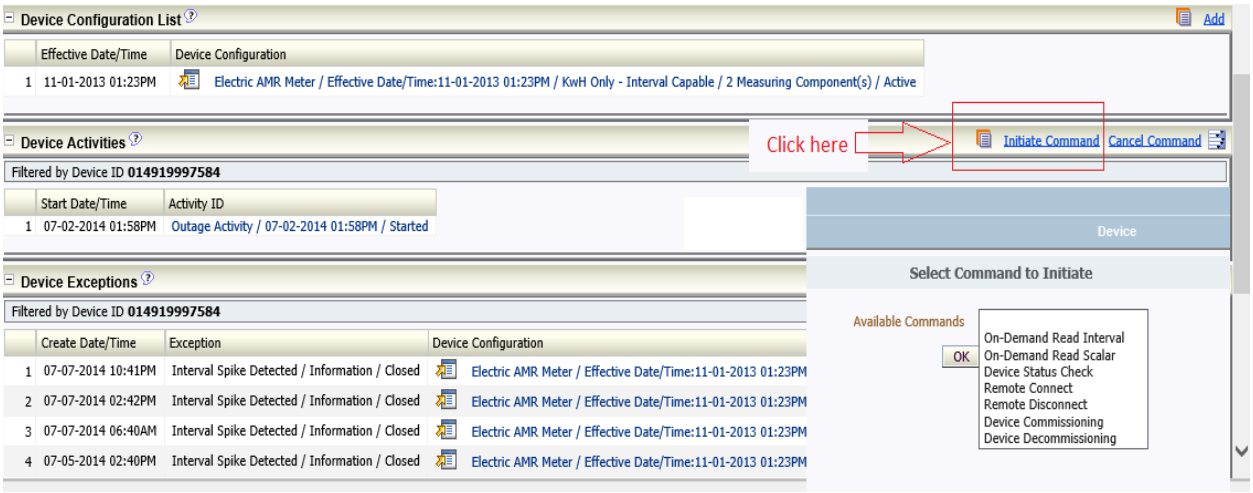


Figure 48: Device Activities

6) Complete the “Remote Connect” and click “save”

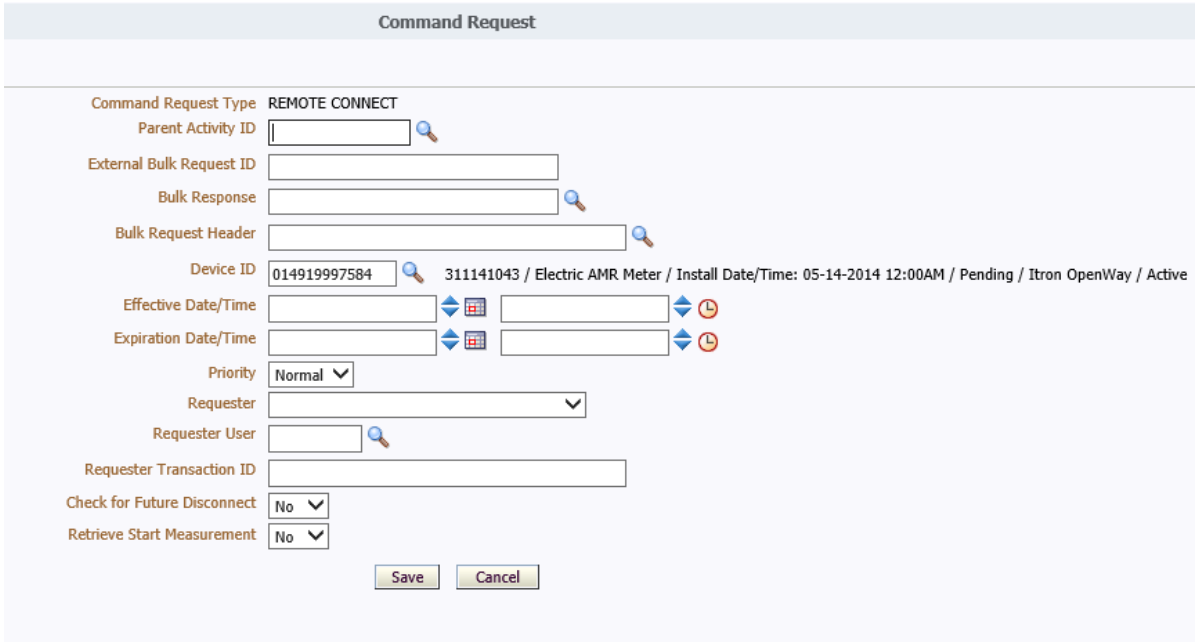


Figure 49: Complete the “Remote Connect”

7) Confirm “Remote Connect” job kicked off

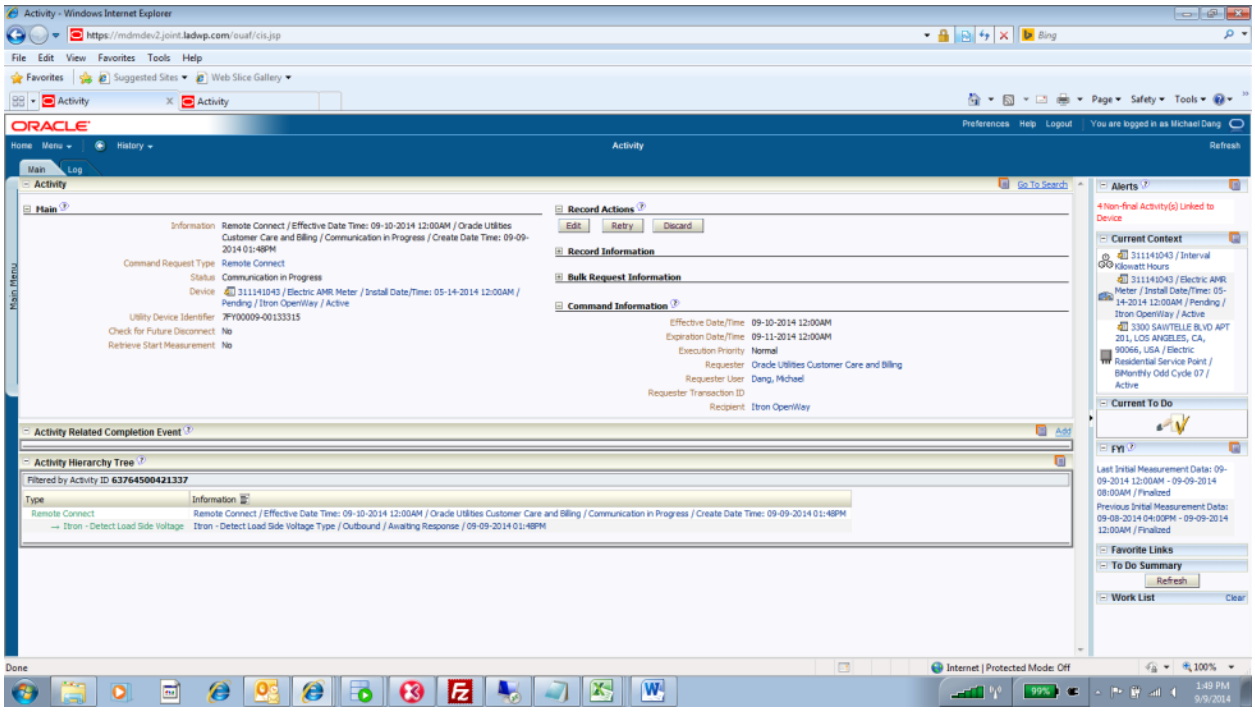


Figure 50: Confirm "Remote Connect" job kicked off

8) Confirmed "Remote Connect" job completed successfully

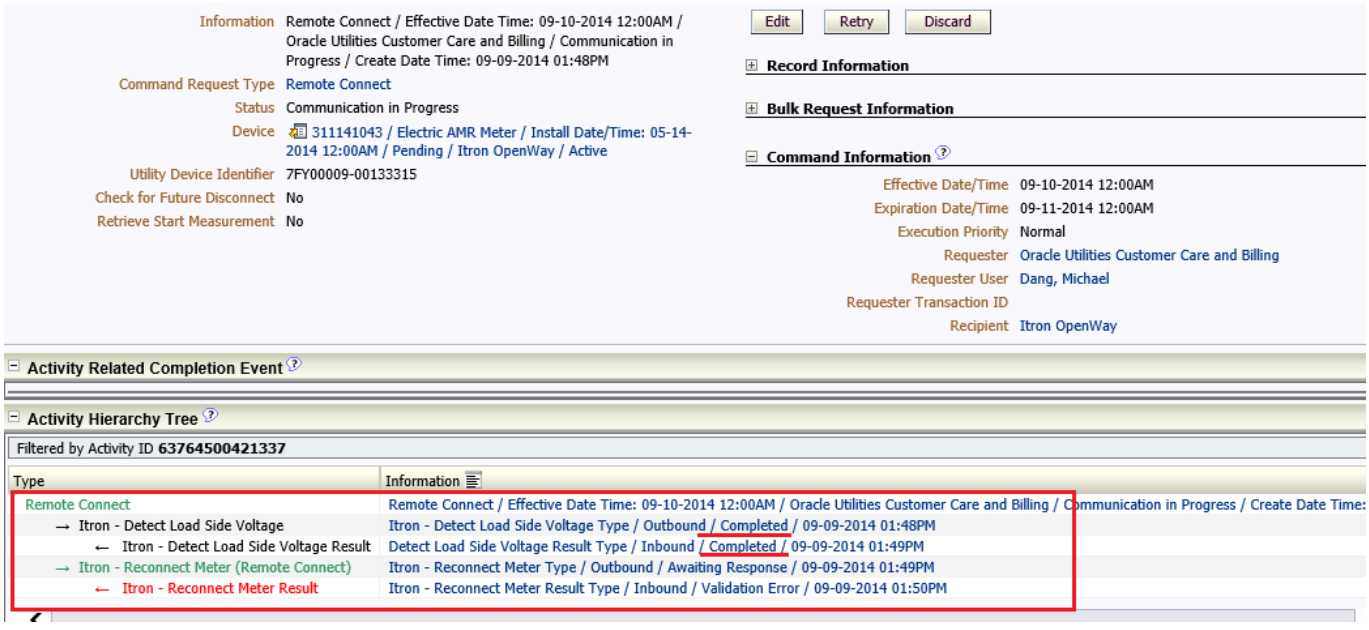


Figure 51: "Remote Connect" job completed successfully

9) Offsite team, Emil Abdelshehid, Afshin Tajian, Shawn Covington, and Josh Sheppard were onsite at UCLA and confirmed that the meter was re-connected



Figure 52: Confirmed that the meter was re-connected

Results from Itron CE confirmed the Remote Connect was successful and processed in 41 seconds.

9/9/2014 1:49 PM request received by the OpenWay Collection Engine, command sent to meter
9/9/2014 1:49 PM meter received the command and executes remote reconnect, event is logged in meter:



Figure 53: Meter log

9/9/2014 1:49 PM response from meter received by OpenWay Collection Engine, status sent to MDM

Job Details Report

Job Details			
Job ID:	1334296	Action:	Connect Endpoint
Request Token:	7bd1bb57-7220-4f0b-a541-6fb4910afefa		
User:	OpenWaySystem	Client IP Address:	10.11.45.51
Group ID:	N/A	# Endpoints:	1
Status:	Successful	Job Duration:	00:00:41
% Complete:	100.0% (1)	Submit Time:	9/9/2014 1:49:18 PM
Start Time:	9/9/2014 1:49:18 PM	Completion Time:	9/9/2014 1:49:59 PM

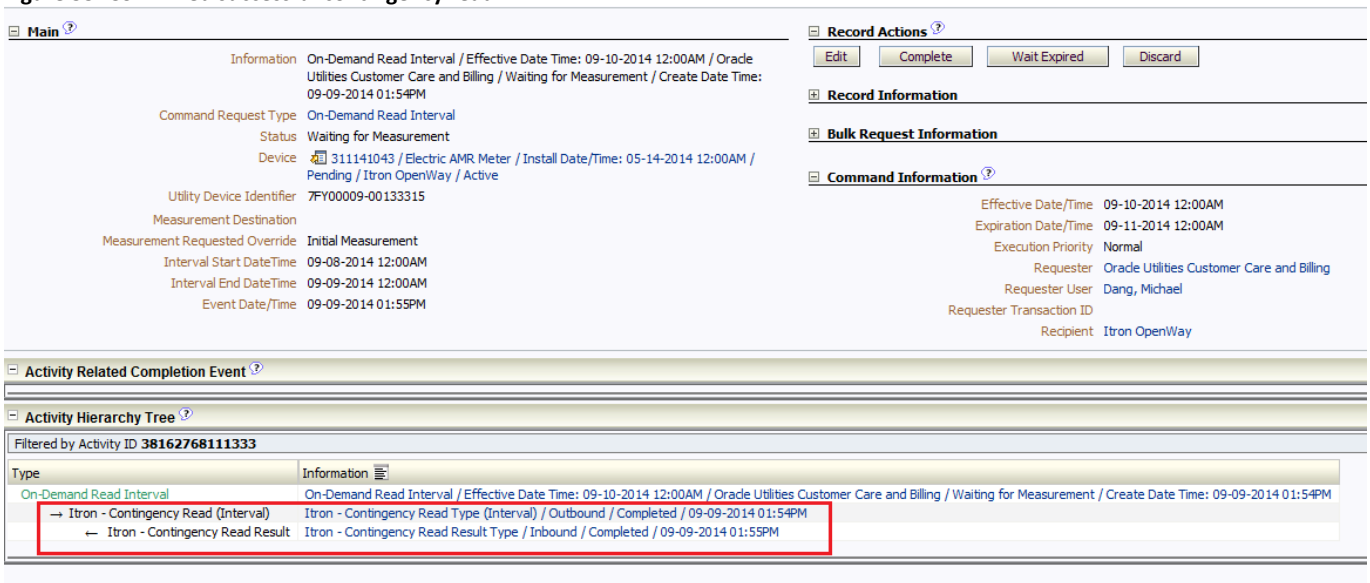
Job Parameters	
RequireUserIntervention:	False

Job Endpoints			
Serial Number	**Field Area Router**	**Job Status**	**Final Result**
	Job Status: Successful (1)		
133315	14555728	Successful	17019 - Job endpoint succeeded.

Figure 54: Job Details Report

10) Requested an on-demand interval read on the meter after a "Remote Connect". Confirmed contingency read was successful.

Figure 55: Confirmed successful contingency read



11) Confirmed in Itron that on demand contingency read was successful

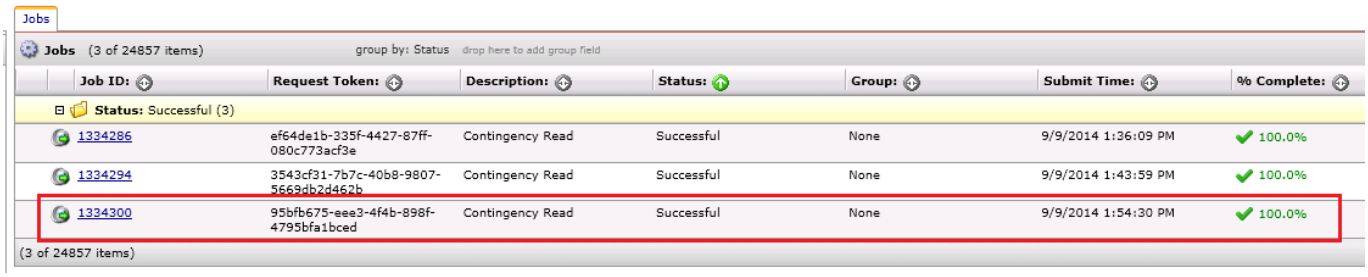


Figure 56: Successful demand contingency read

12) Also obtained meter register data from Itron CE following the remote connect/disconnect test to confirm no issues with the meter


```
<?xml version="1.0" encoding="US-ASCII"?>
<edl xmlns="http://www.nema.org/tdl/NEMA.73.84.82.68/EDLSchema" version="2.5" deviceClass="73.84.82.68">
  <data>
    <GEN_CONFIG_TBL>
      <FORMAT_CONTROL_1>
        <DATA_ORDER>0</DATA_ORDER>
        <CHAR_FORMAT>1</CHAR_FORMAT>
        <MODEL_SELECT>0</MODEL_SELECT>
        <FILLER>0</FILLER>
      </FORMAT_CONTROL_1>
      <FORMAT_CONTROL_2>
        <TM_FORMAT>3</TM_FORMAT>
        <DATA_ACCESS_METHOD>1</DATA_ACCESS_METHOD>
        <ID_FORM>0</ID_FORM>
        <INT_FORMAT>0</INT_FORMAT>
      </FORMAT_CONTROL_2>
      <FORMAT_CONTROL_3>
        <NI_FORMAT1>0</NI_FORMAT1>
        <NI_FORMAT2>1</NI_FORMAT2>
      </FORMAT_CONTROL_3>
      <DEVICE_CLASS binary="49545244"/>
      <NAMEPLATE_TYPE>2</NAMEPLATE_TYPE>
      <DEFAULT_SET_USED>0</DEFAULT_SET_USED>
      <MAX_PROC_PARM_LENGTH>44</MAX_PROC_PARM_LENGTH>
      <MAX_RESP_DATA_LEN>42</MAX_RESP_DATA_LEN>
      <STD_VERSION_NO>2</STD_VERSION_NO>
      <STD_REVISION_NO>0</STD_REVISION_NO>
      <DIM_STD_TBLS_USED>16</DIM_STD_TBLS_USED>
      <DIM_MFG_TBLS_USED>48</DIM_MFG_TBLS_USED>
      <DIM_STD_PROC_USED>4</DIM_STD_PROC_USED>
      <DIM_MFG_PROC_USED>21</DIM_MFG_PROC_USED>
      <DIM_MFG_STATUS_USED>5</DIM_MFG_STATUS_USED>
      <NBR_PENDING>8</NBR_PENDING>
      <STD_TBLS_USED>
        <entry index="0-8,11-16,21-28,31-34,41-44,46,51-55,61-64,71-76,120-123,125-127">true</entry>
        <entry index="9-10,17-20,29-30,35-40,45,47-50,56-60,65-70,77-119,124">false</entry>
      </STD_TBLS_USED>
      <MFG_TBLS_USED>
        <entry index="0-3,5-9,13-22,26-36,40-42,50-62,64-88,90-95,100-116,120,127,130-133,142-147,150-156,158-160,171-172,180-189,191-195,200
          -201,212-218,220-224,230-249,312,320-322,331,334-335,341-346,361-363,365,369-371,373-375">true</entry>
```


Figure 57: Meter register data

Test results for Remote Connect - Pass

8. **Select at least 2 meters at LADWP lab environment. Coordinate with LADWP, and issue Remote-Reconnect commands to meters at least once during the test.**

   Action: Following meters were selected

   1) UCLA Meter: 7FY00009-00133315 ESN2.16.840.1.114416.1.24. 133315

   2) Test Meter: 7F00009-1452194

   ESN - 2.16.840.1.114416.1.24.1452194

   Acceptance Criteria: Remote Connect to be performed successfully.

   Date: 9/9/2014 and 10/16/2014

   Result: Passed, based on following outcomes

9/9/2014: Remote Connect Testing

Tester: Thuy-An, Michael

Witnesses: Emil, Afshin, Shawn and Josh

Test using meter with batch number: 7FY00009-00133315 with ESN**2.16.840.1.114416.1.24. 133315**

Account	WR No	Premise ID	Type	Classification	Address	New Meter Prefix	New Meter Size	New Meter Number	New Meter Serial Number	Old Meter Prefix	Old Meter Size	Old Meter Number	Date Completed	FI-39 RMVD KWH READ	FQ-41 RMVD KWD READ
	1360493	2068271458	NBRAC	SG-AMI-D	3300 SAWTELLE BLUNIT: 201 LOS ANGELES	7FY	9	133315	311141043	Y	9	53489	5/14/2014	40921	

Figure 58: ESN2.16.840.1.114416.1.24. 133315



Figure 59: Meter - ESN2.16.840.1.114416.1.24. 133315

Test Steps for Remote Connect

1) Navigate to Menu, click on Main Menu, drop down to Device and click on +Device
2) Select Device Identifier Type and choose Badge number and enter in 7FY00009-00133315 and click refresh

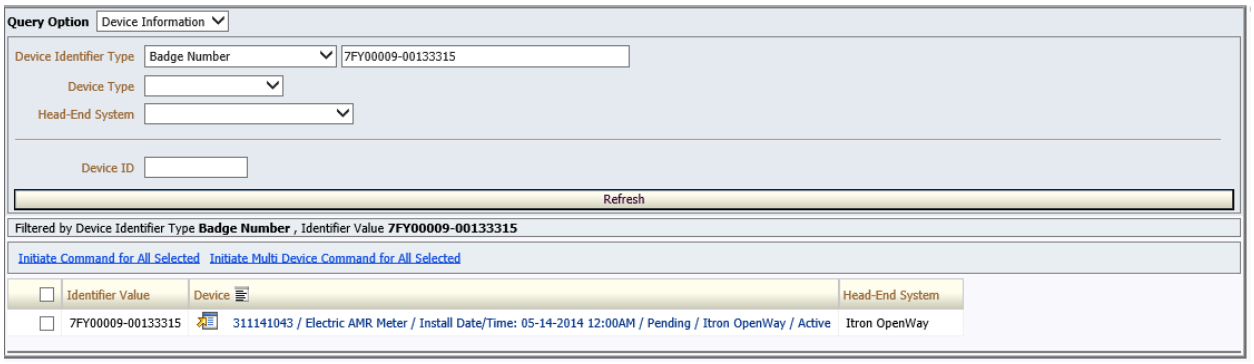


Figure 60: Menu for Remote Connect

3) Click on meter below and confirm badge number and ESN for meter

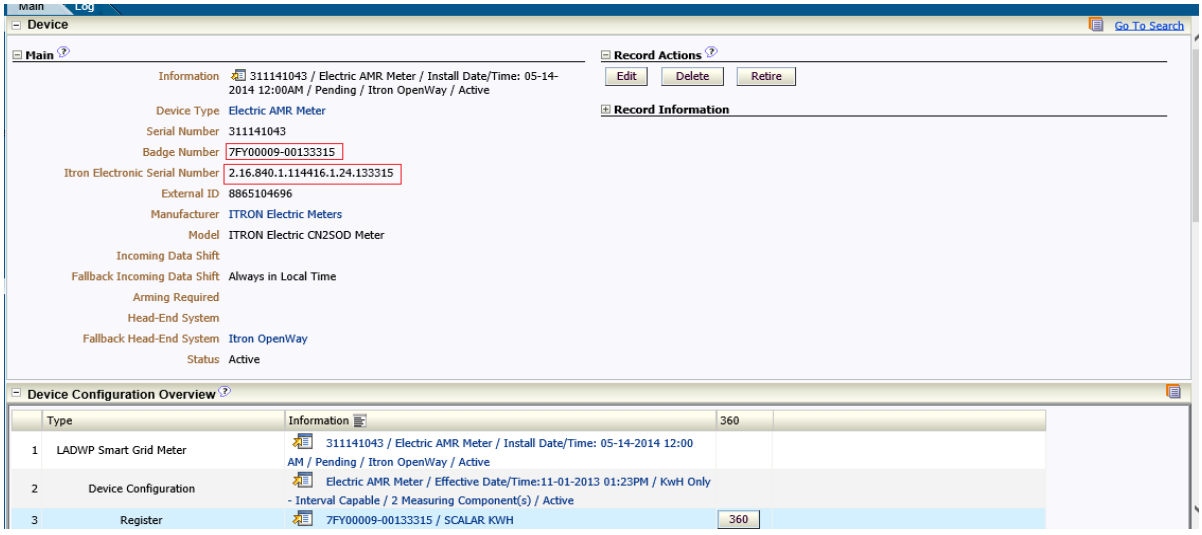


Figure 61: Confirm badge number and ESN for meter

4) Click on Service Point and confirm the meter address location matches that of 3300 SAWTELLE BL UNIT: 201

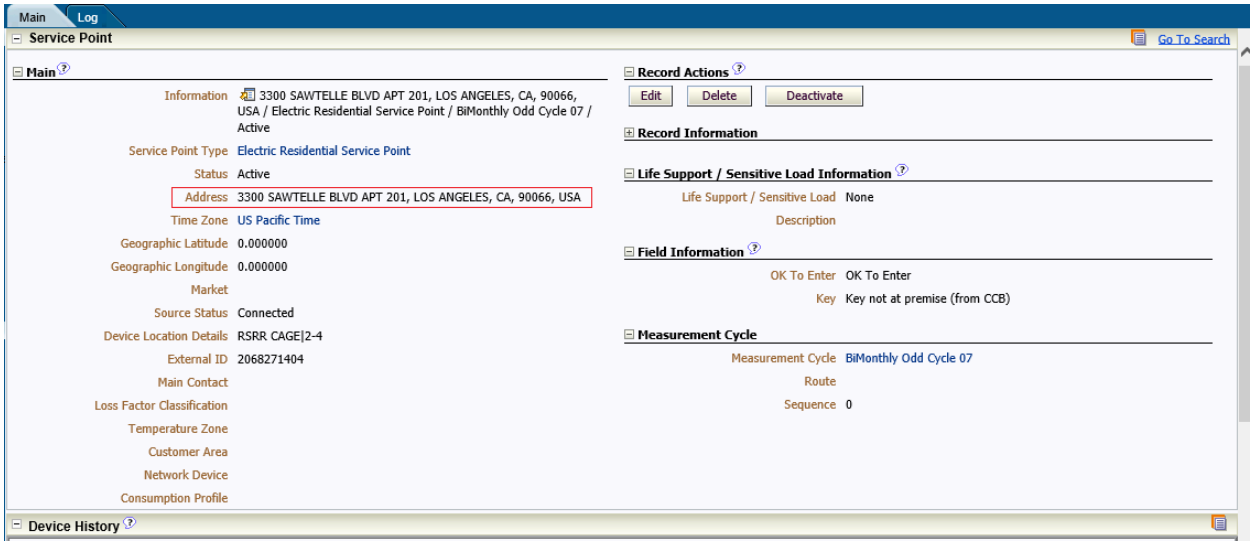


Figure 62: Service Point

5) From Device, scroll down to Device Activities and click on “Initiate Command” and then from drop down select Remote Connect and click “ok”

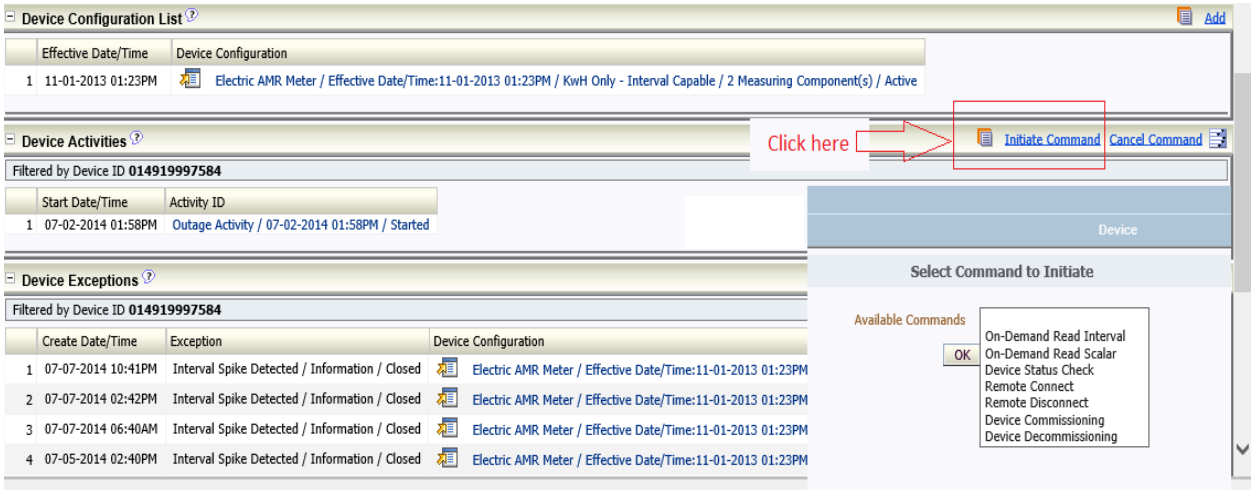


Figure 63: Initiate Command

6) Complete the “Remote Connect” and click “save”

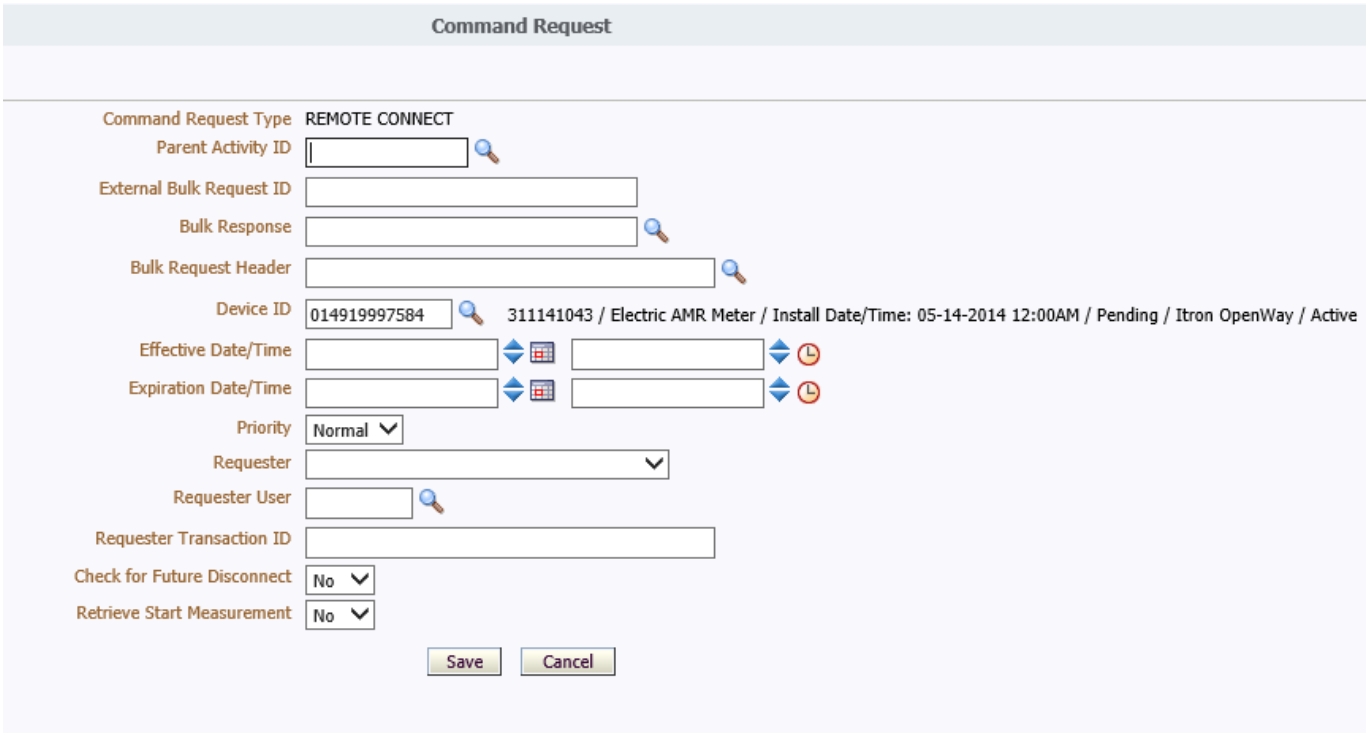


Figure 64: Command Request

7) Confirm “Remote Connect” job kicked off

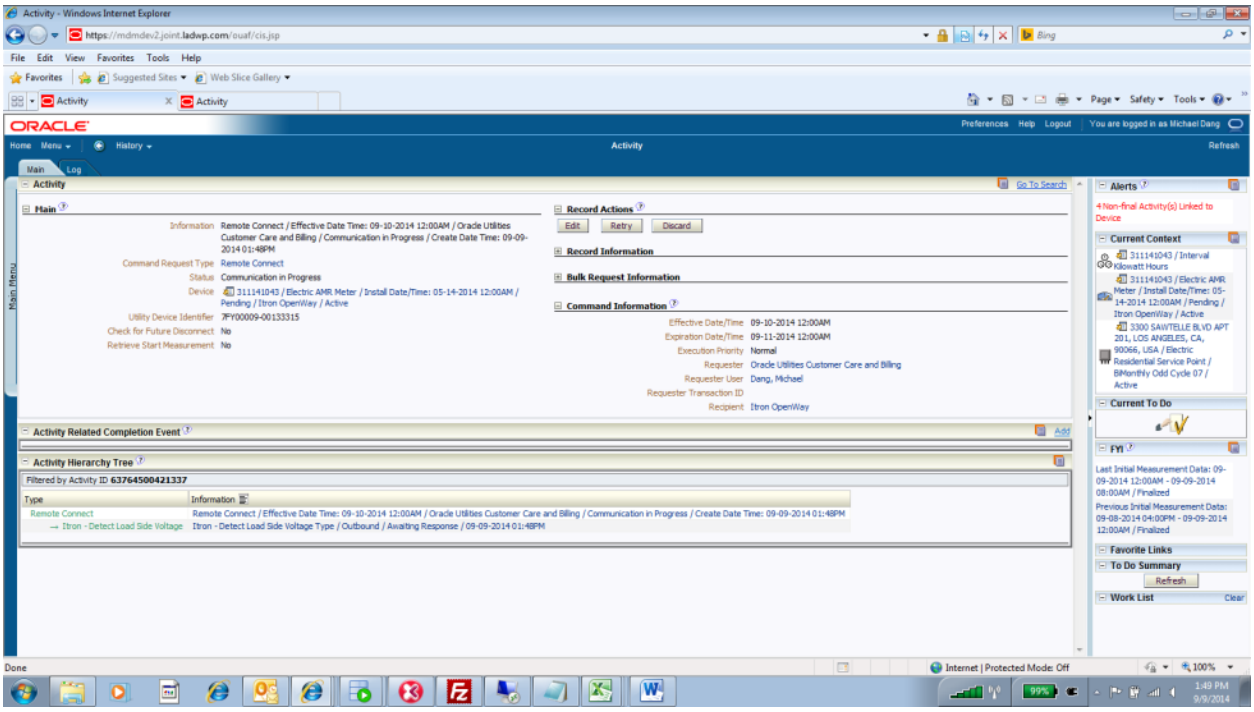


Figure 65: Job kick off

8) Confirmed "Remote Connect" job completed successfully

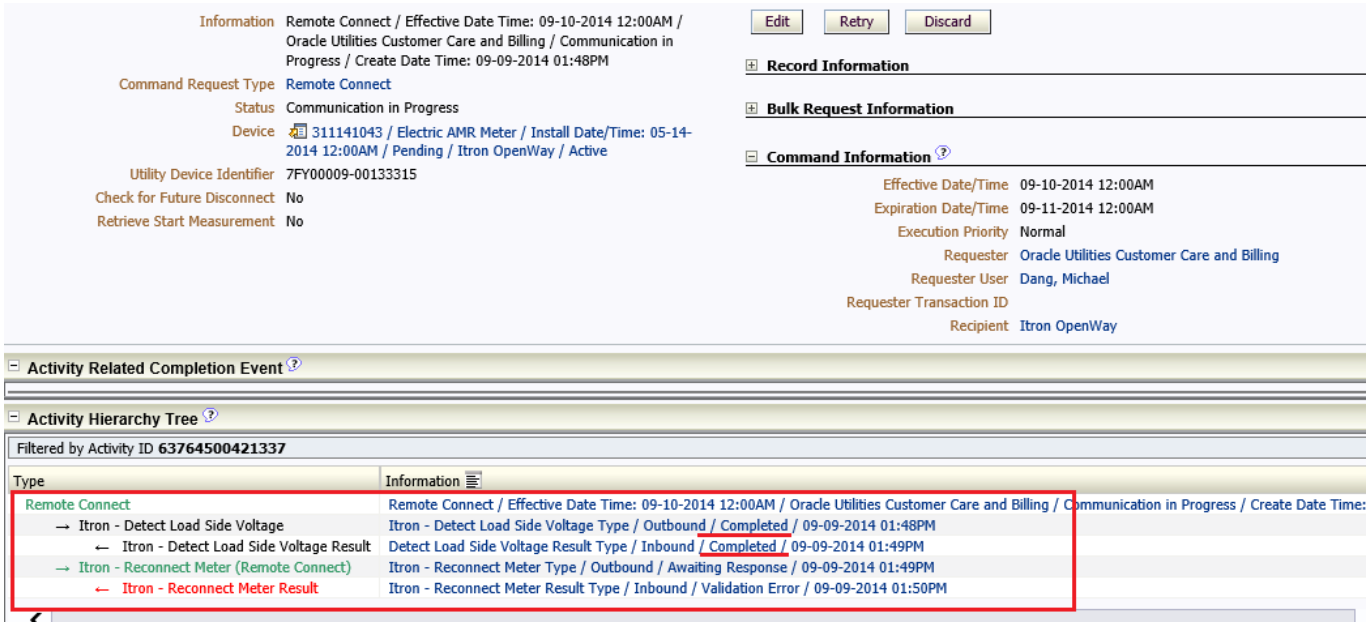


Figure 66: Completion Event

9) Offsite team, Emil, Afshin, Shawn & Josh was onsite at UCLA and confirmed that the meter was re-connected



Figure 67: Result on meter

Results from Itron CE confirmed the Remote Connect was successful and processed in 41 seconds.

9/9/2014 1:49 PM request received by the OpenWay Collection Engine, command sent to meter
9/9/2014 1:49 PM meter received the command and executes remote reconnect, event is logged in meter:

History Log

Event Date/Time:	Event:
9/9/2014 1:32:29 PM	Remote disconnect success
9/9/2014 1:49:53 PM	Remote connect success

Figure 68: History log - Connect & Disconnect

9/9/2014 1:49 PM response from meter received by OpenWay Collection Engine, status sent to MDM

Job Details Report

Job Details			
Job ID:	1334296	Action:	Connect Endpoint
Request Token:	7bd1bb57-7220-4f0b-a541-6fb4910afefa		
User:	OpenWaySystem	Client IP Address:	10.11.45.51
Group ID:	N/A	# Endpoints:	1
Status:	Successful	Job Duration:	00:00:41
% Complete:	100.0% (1)	Submit Time:	9/9/2014 1:49:18 PM
Start Time:	9/9/2014 1:49:18 PM	Completion Time:	9/9/2014 1:49:59 PM

Job Parameters	
RequireUserIntervention:	False

Job Endpoints			
Serial Number	**Field Area Router**	**Job Status**	**Final Result**
	Job Status: Successful (1)		
133315	14555728	Successful	17019 - Job endpoint succeeded.

Figure 69: Final Result

10) Requested an on-demand interval read on the meter after a “Remote Connect”. Confirmed contingency read was successful.

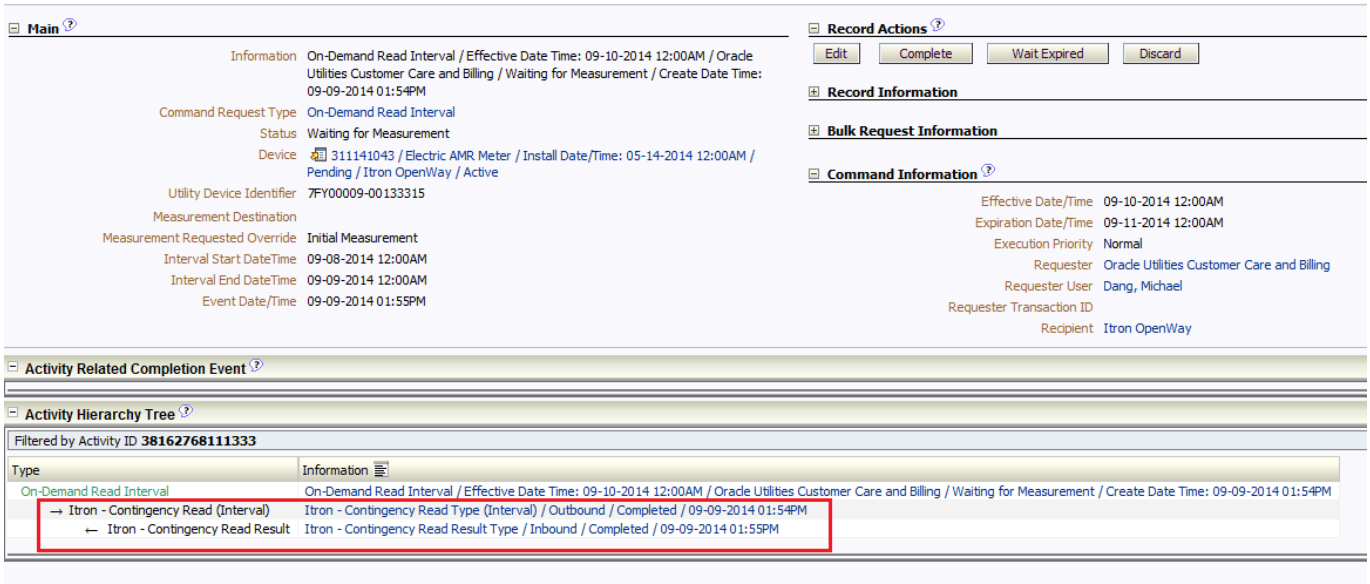


Figure 70: Successful Contingency Read

11) Confirmed in Itron that on demand contingency read was successful

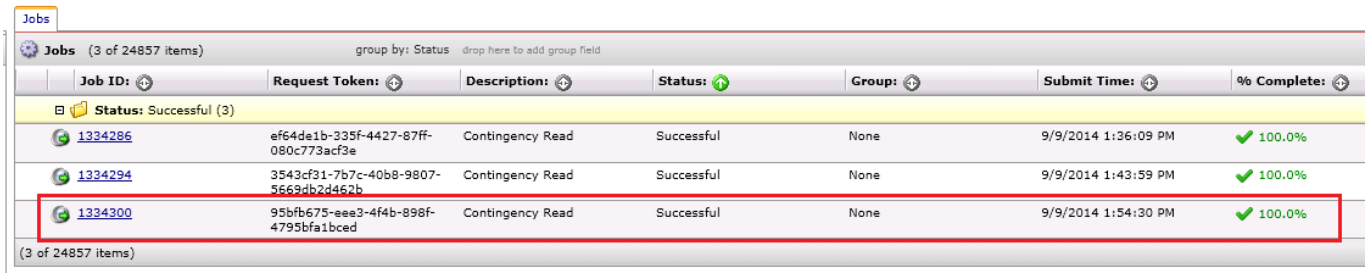


Figure 71: Successful on Demand Contingency Read

12) Also obtained meter register data from Itron CE following the remote connect/disconnect test to confirm no issues with the meter


```
<?xml version="1.0" encoding="US-ASCII"?>
- <edl xmlns="http://www.nema.org/tdl/NEMA.73.84.82.68/EDLSchema" version="2.5" deviceClass="73.84.82.68">
  - <data>
    - <GEN_CONFIG_TBL>
      - <FORMAT_CONTROL_1>
          <DATA_ORDER>0</DATA_ORDER>
          <CHAR_FORMAT>1</CHAR_FORMAT>
          <MODEL_SELECT>0</MODEL_SELECT>
          <FILLER>0</FILLER>
        </FORMAT_CONTROL_1>
      - <FORMAT_CONTROL_2>
          <TM_FORMAT>3</TM_FORMAT>
          <DATA_ACCESS_METHOD>1</DATA_ACCESS_METHOD>
          <ID_FORM>0</ID_FORM>
          <INT_FORMAT>0</INT_FORMAT>
        </FORMAT_CONTROL_2>
      - <FORMAT_CONTROL_3>
          <NI_FORMAT1>0</NI_FORMAT1>
          <NI_FORMAT2>1</NI_FORMAT2>
        </FORMAT_CONTROL_3>
        <DEVICE_CLASS binary="49545244"/>
        <NAMEPLATE_TYPE>2</NAMEPLATE_TYPE>
        <DEFAULT_SET_USED>0</DEFAULT_SET_USED>
        <MAX_PROC_PARM_LENGTH>44</MAX_PROC_PARM_LENGTH>
        <MAX_RESP_DATA_LEN>42</MAX_RESP_DATA_LEN>
        <STD_VERSION_NO>2</STD_VERSION_NO>
        <STD_REVISION_NO>0</STD_REVISION_NO>
        <DIM_STD_TBLS_USED>16</DIM_STD_TBLS_USED>
        <DIM_MFG_TBLS_USED>48</DIM_MFG_TBLS_USED>
        <DIM_STD_PROC_USED>4</DIM_STD_PROC_USED>
        <DIM_MFG_PROC_USED>21</DIM_MFG_PROC_USED>
        <DIM_MFG_STATUS_USED>5</DIM_MFG_STATUS_USED>
        <NBR_PENDING>8</NBR_PENDING>
      - <STD_TBLS_USED>
          <entry index="0-8,11-16,21-28,31-34,41-44,46,51-55,61-64,71-76,120-123,125-127">true</entry>
          <entry index="9-10,17-20,29-30,35-40,45,47-50,56-60,65-70,77-119,124">false</entry>
        </STD_TBLS_USED>
      - <MFG_TBLS_USED>
          <entry index="0-3,5-9,13-22,26-36,40-42,50-62,64-88,90-95,100-116,120,127,130-133,142-147,150-156,158-160,171-172,180-189,191-195,200
            -201,212-218,220-224,230-249,312,320-322,331,334-335,341-346,361-363,365,369-371,373-375">true</entry>
          <entry index="4,10-12,23-25,37-39,43-49,63,89,96-99,117-119,121-126,128-129,134-141,148-149,157,161-170,173-179,190,196-199,202-
```


Figure 72: No issues in meter register data

Test results for Remote Connect - Pass

9/16/2014: Remote Re-Connect Testing

Tester: Josh Sheppard

Witnesses: Thuy-An Nguyen

Verification: Afshin Tajian

Test using meter with batch number: 7F00009-1452194 with ESN 2.16.840.1.114416.1.24.1452194 and confirmed that meter was disconnected



Figure 73: Disconnected meter

Test Steps for Remote Connect

1) Navigate to Menu, click on Main Menu, drop down to Device and click on +Device
2) Select Device Identifier Type and choose Badge number and enter in %1452194 and click refresh
3) Confirm full badge number 7F00009-1452194 matches with that on meter

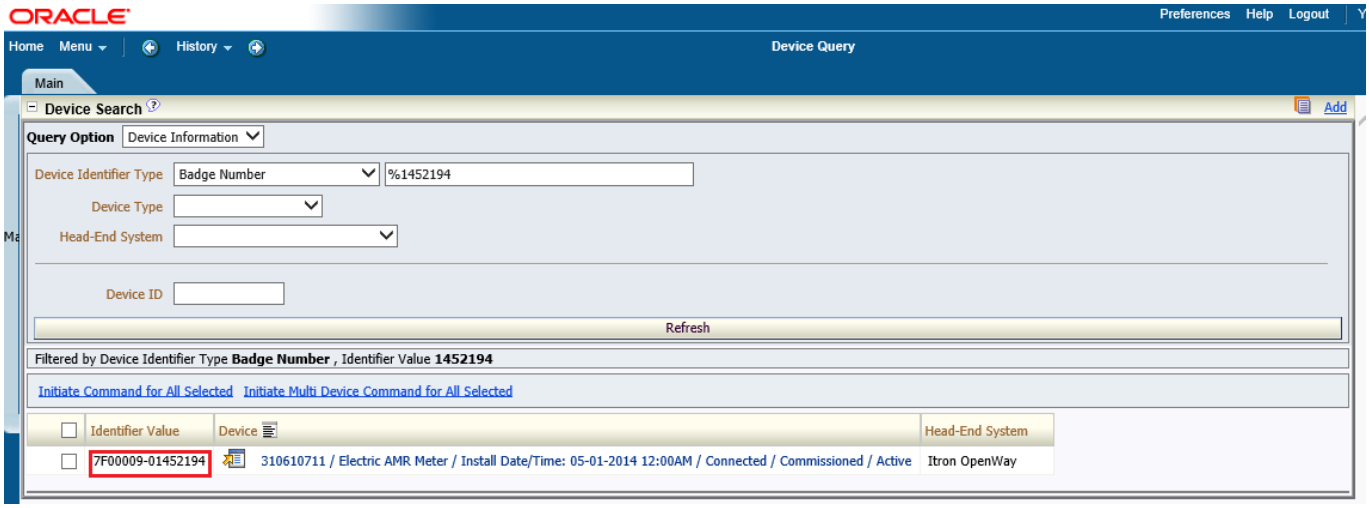


Figure 74: Verify badge number

4) Click on meter below and confirm badge number and ESN for meter

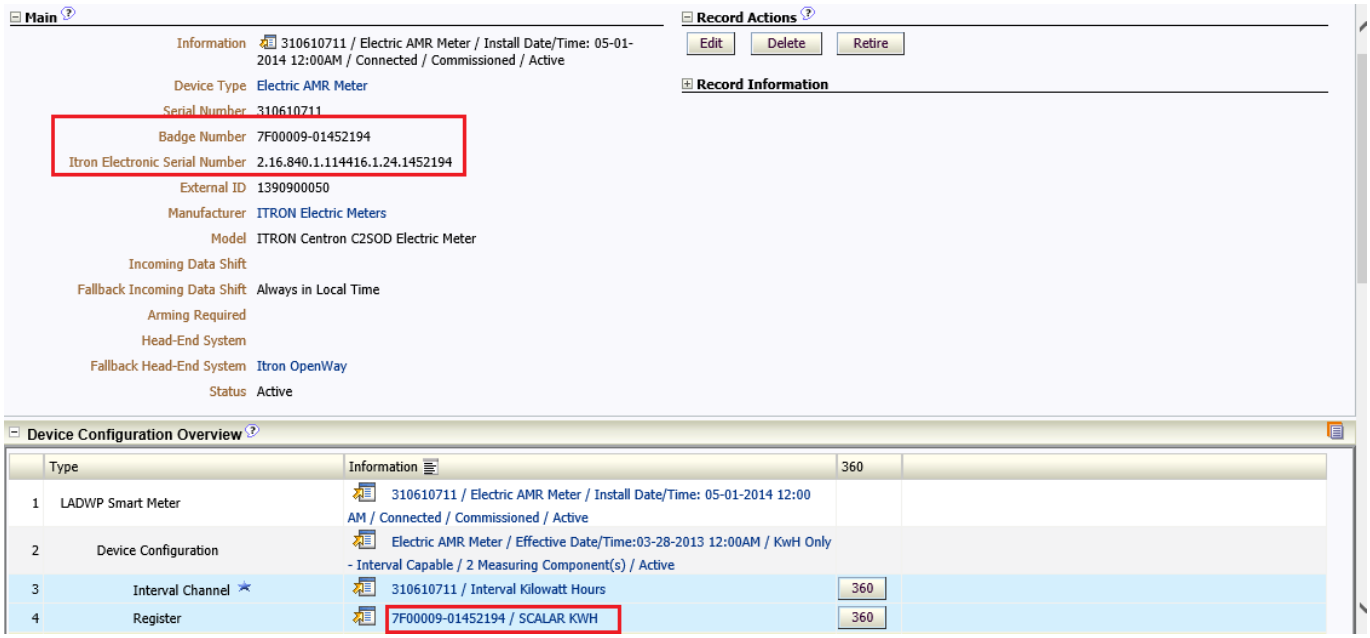


Figure 75: Verify ESN

5) Click on Service Point and confirm the meter address location matches that of 111 N Hope Street#800, Los Angeles, CA 91776 (one of our Residential Test Meters – Aras Desk)

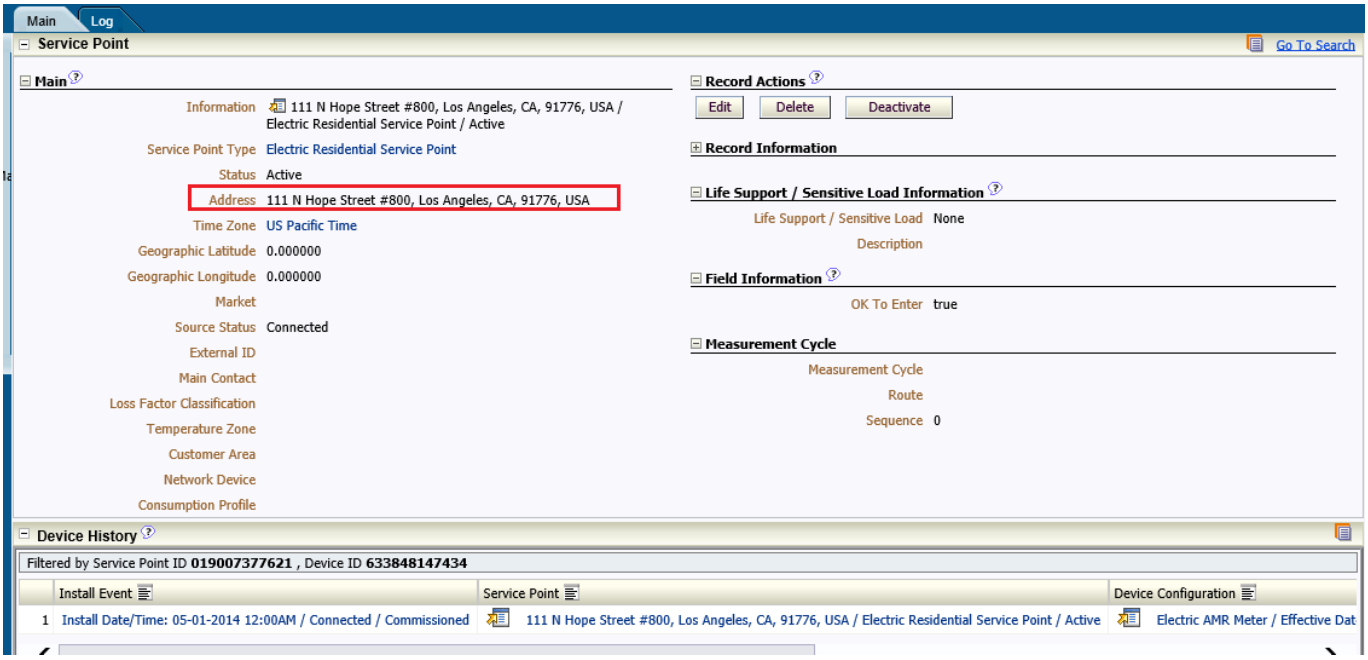


Figure 76: Verify meter location

6) From Device, scroll down to Device Activities and click on “Initiate Command” and then from drop down select Remote Connect and click “ok”

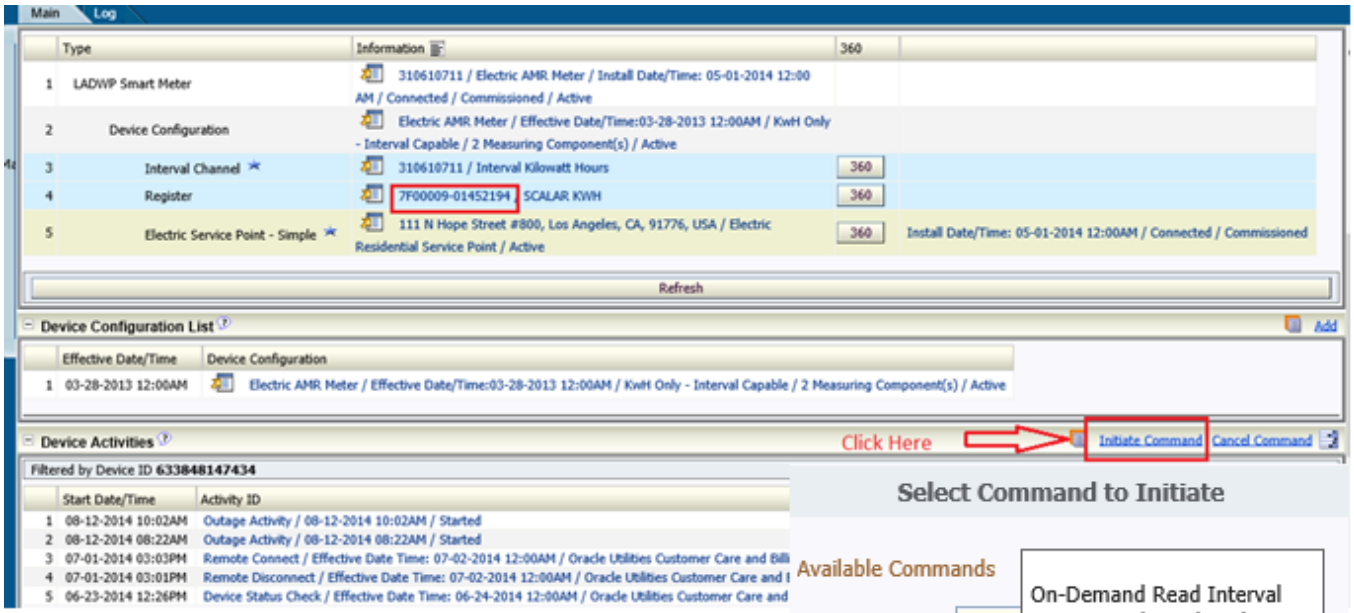


Figure 77: Initiate Command

7) Complete the “Remote Connect” and click “save”

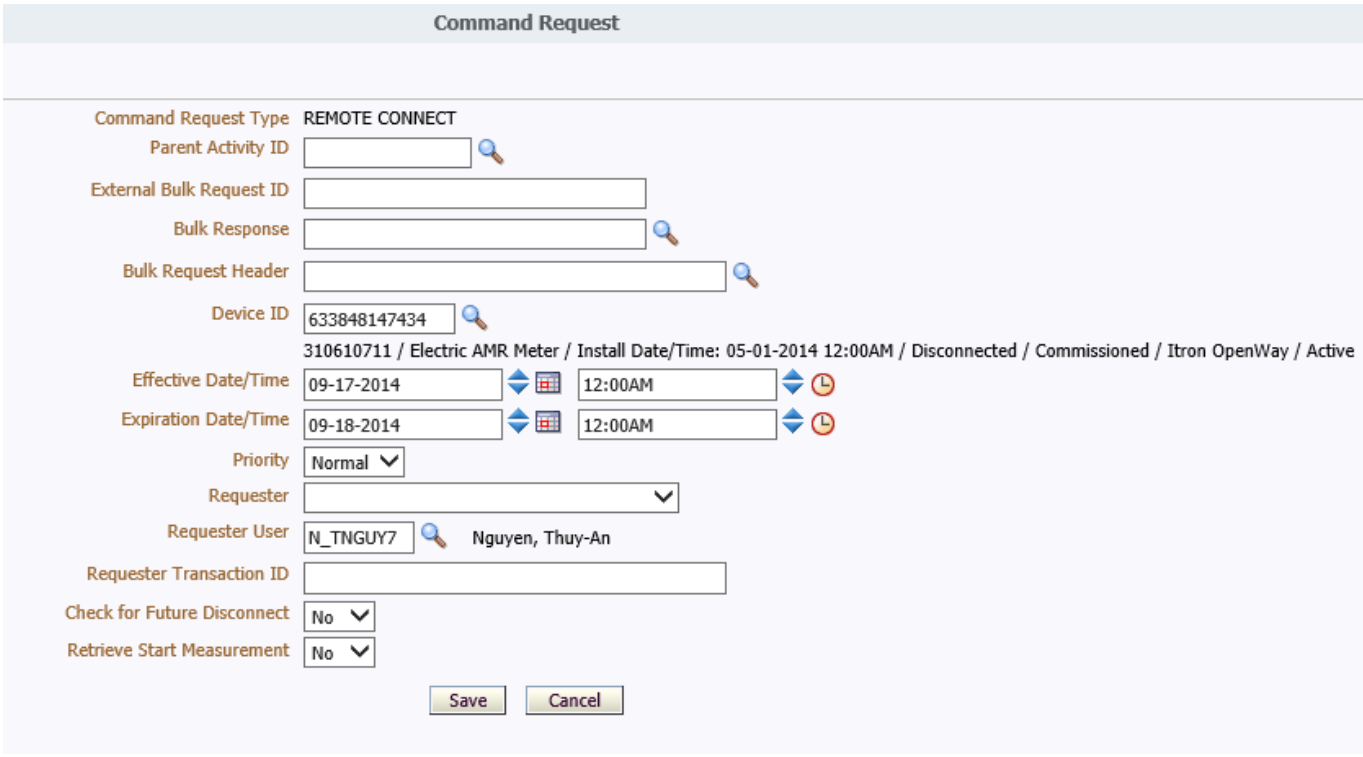


Figure 78: Command Request

8) Click on “Connect”

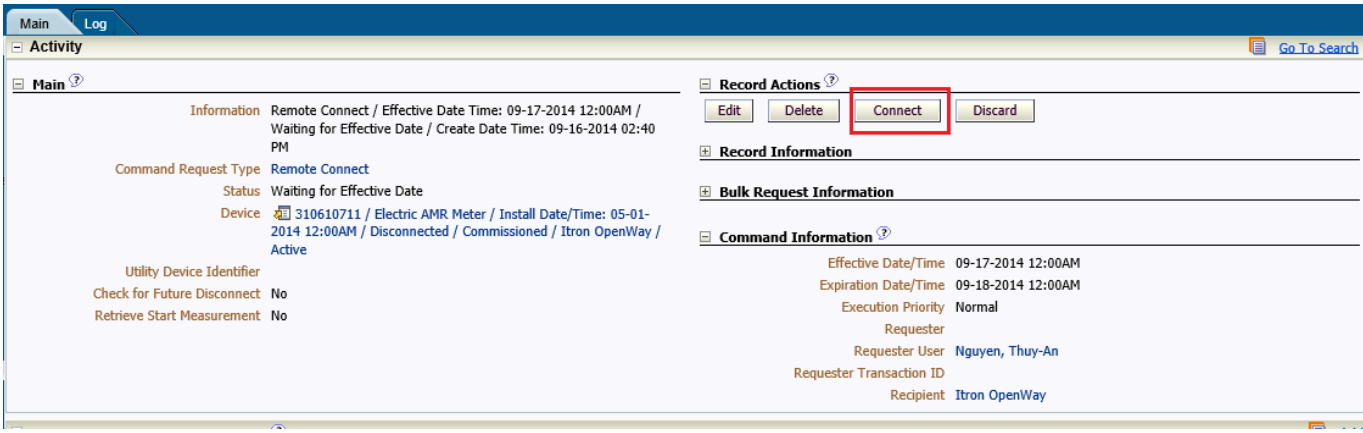


Figure 79: Activity - connect

9) Confirm that re-connect job completed in MDM

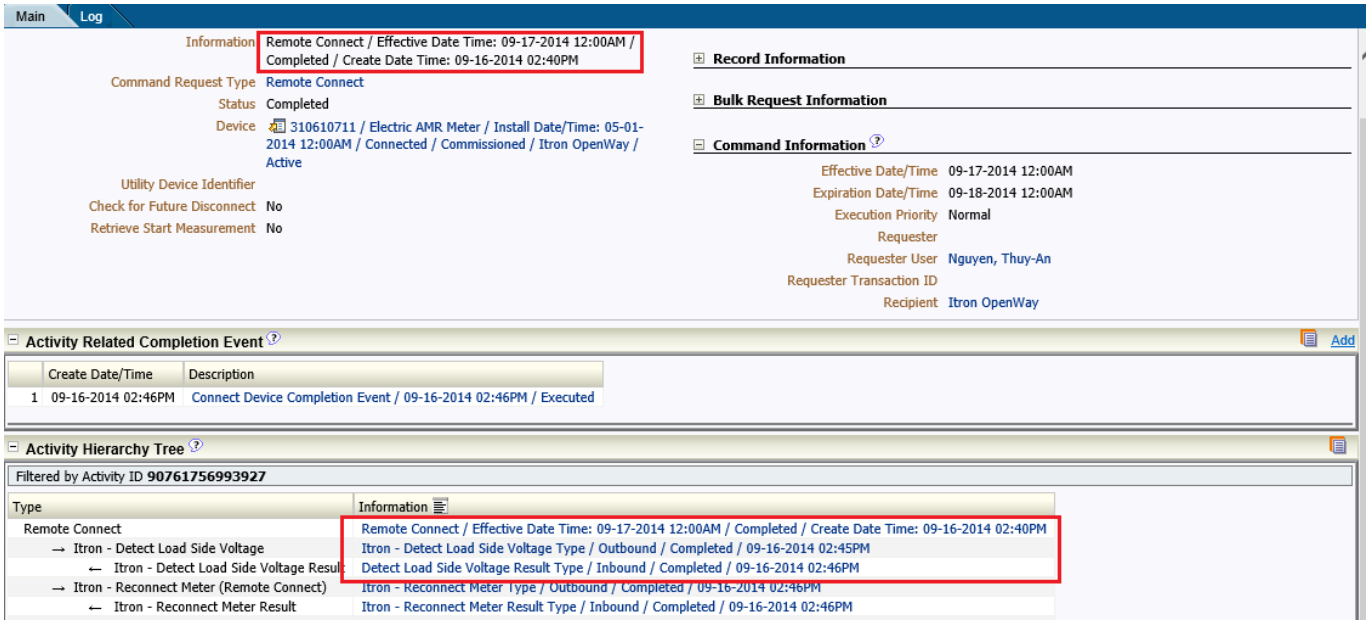


Figure 80: Confirm re-connect

10) Josh and Thuy-An confirmed that the meter display is now reconnected

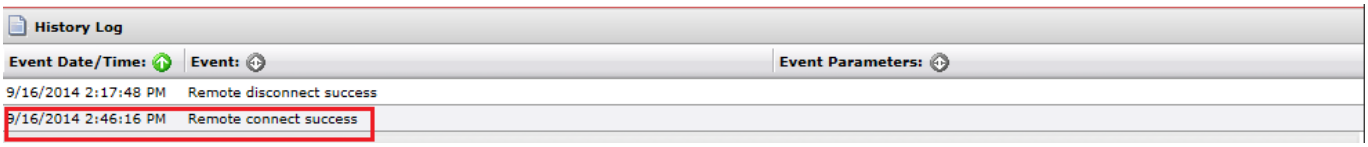


Figure 81: Processed

Results from Itron CE confirmed the Remote Connect was successful and processed in 21 seconds.

9/16/2014 2:46:04 PM request received by the OpenWay Collection Engine, command sent to meter

9/16/2014 2:46:16 PM meter received the command and executes remote disconnect, event is logged in meter:



History Log

Event Date/Time:	Event:	Event Parameters:
9/16/2014 2:17:48 PM	Remote disconnect success	
9/16/2014 2:46:16 PM	Remote connect success	

Figure 82: Remote connect success in history log

Job Details			
Job ID:	1341064	Action:	Connect Endpoint
Request Token:	07dc3ca2-a3eb-40d7-bca1-cbc036dd93fa		
User:	OpenWaySystem	Client IP Address:	10.11.45.51
Group ID:	N/A	# Endpoints:	1
Status:	Successful	Job Duration:	00:00:12
% Complete:	100.0% (1)	Submit Time:	9/16/2014 2:46:04 PM
Start Time:	9/16/2014 2:46:04 PM	Completion Time:	9/16/2014 2:46:16 PM

Job Parameters	
RequireUserIntervention:	False

Job Endpoints			
Serial Number	**Field Area Router**	**Job Status**	**Final Result**
	Job Status: Successful (1)		
1452194	14555232	Successful	17019 - Job endpoint succeeded.

Figure 83: Confirm in Job Details

11) Requested an on-demand interval read on the meter after a “Remote Connect”.

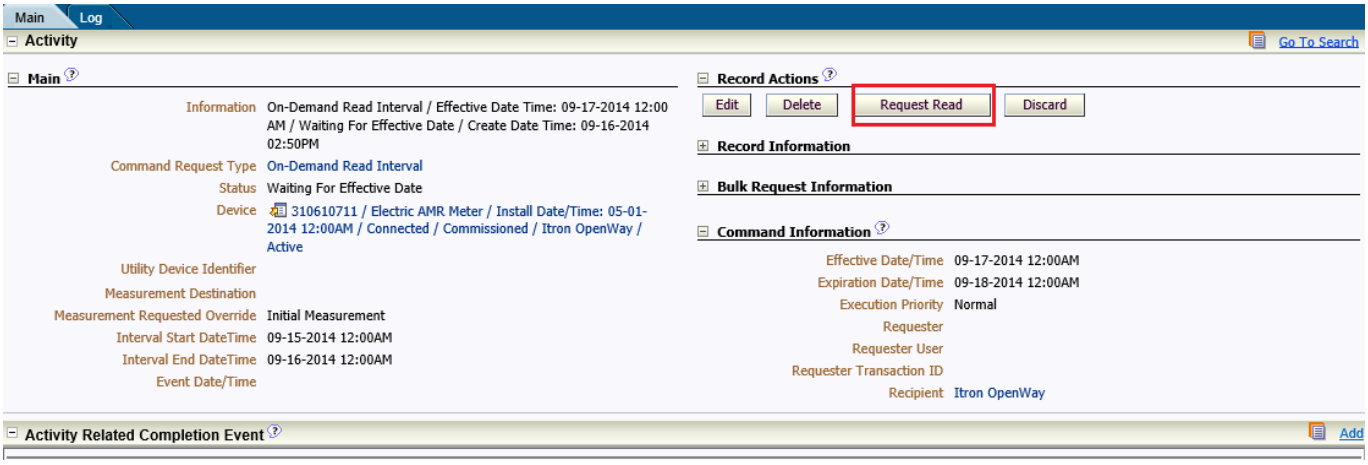


Figure 84: On-demand interval read request

12) Confirmed contingency read was successful.

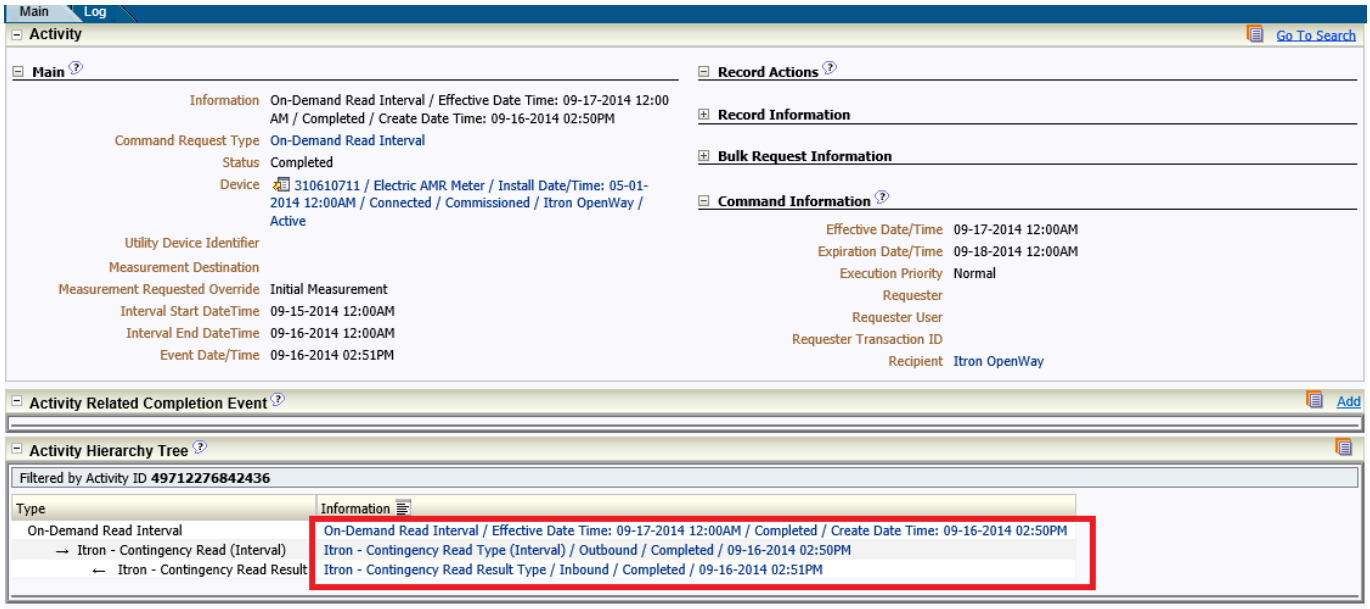


Figure 85: Activity Hierarchy Tree

13) Confirmed in Itron that on demand contingency read was successful

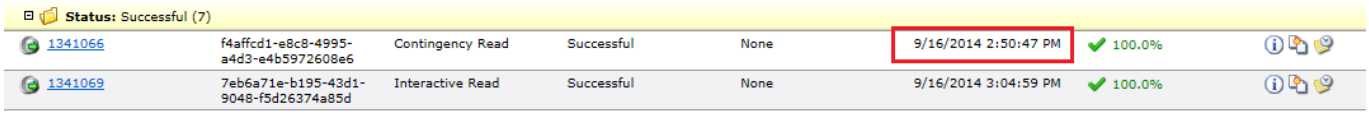


Figure 86: Successful status

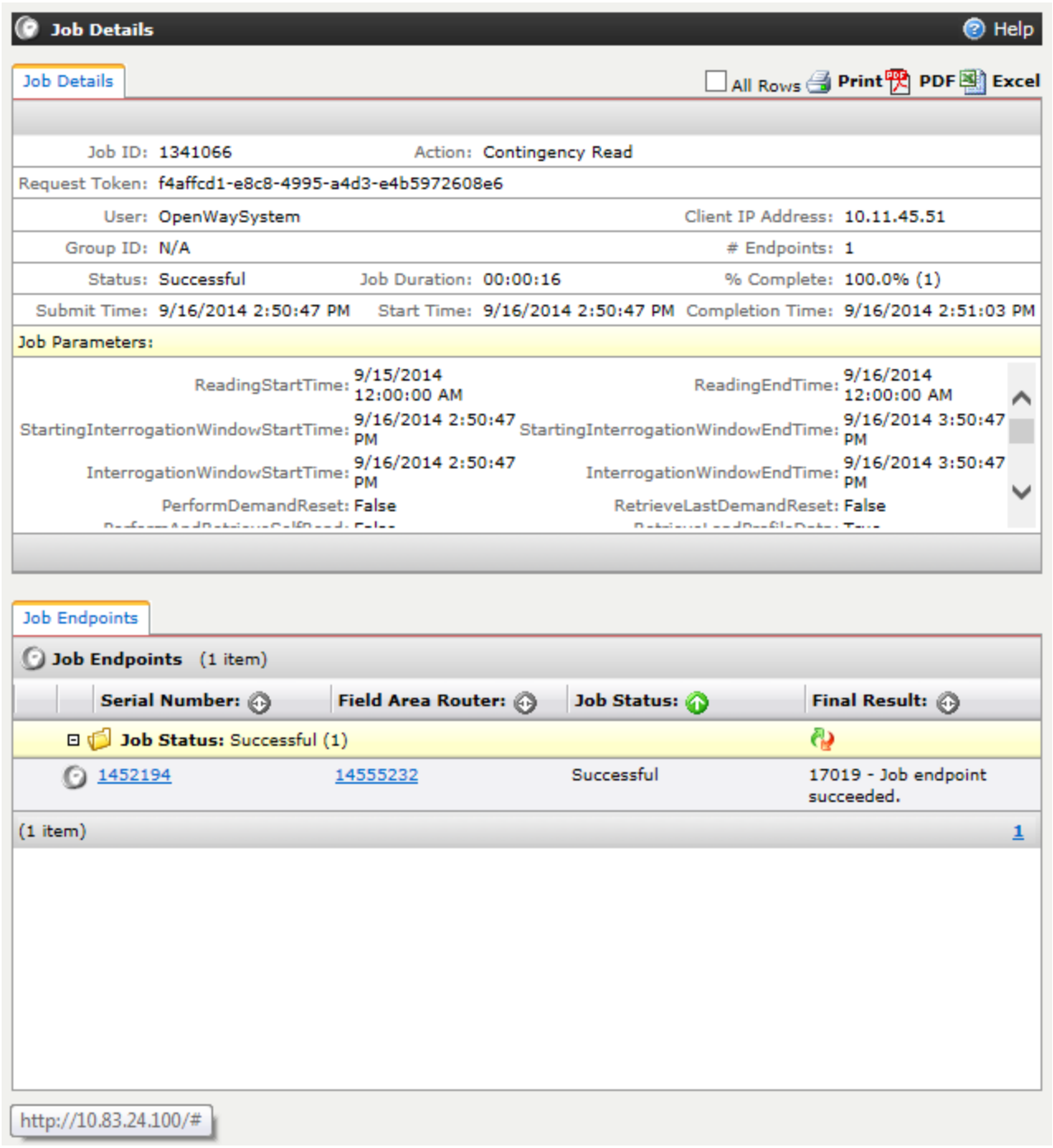


Figure 87: Final result of job status

Part 5: Gap Fill Testing

Purpose

The objective is to capture the test results of validating that Itron OpenWay Collection Engine supports a gap fill concept, called Automated Missed Read Retry.

Summary

Los Angeles Department of Water and Power (LADWP) has installed 51,190 AMI meters. Using Oracle MDM, these meters are read 3 times a day at the respective time of 8:05 am, 4:05 pm, and 12:05 am. Each interrogation includes a request for load profile, registers and meter events for the prior 8 hours. On any given day, there is a 3-8% meter failure response rate. LADWP's goal is to achieve 100% readings for each meter to ensure billing accuracy in the near future. As such, LADWP would like to validate that Itron OpenWay Collection Engine is capable of handling gap fill reads.

Itron OpenWay Collection Engine supports a gap fill concept, called Automated Missed Read Retry. If there is a missed Interrogation request, the Collection Engine will "create" a pending Contingency Read for the meter. The parameters for the Contingency Read request will be equal to the missed Interrogation request, meaning if load profile and events were requested as part of Interrogation, then load profile and events will be requested as part of Contingency Read request. The created Contingency Read request is held by the OpenWay Collection Engine until the meters respond to the current Interrogation request, if the meter does not respond to the current running Interrogation request the OpenWay Collection Engine does not submit the Contingency Read request. Currently, Itron OpenWay Collection Engine is capable of handling gap fill reads for only up to the past 30 days.

Details of the Test

The test was conducted using MDMDev2 v2.1 against the Test Collection Engine v6.6. Below are the overall high-level test steps:

1. Select "App All Test" Group in Collection Engine

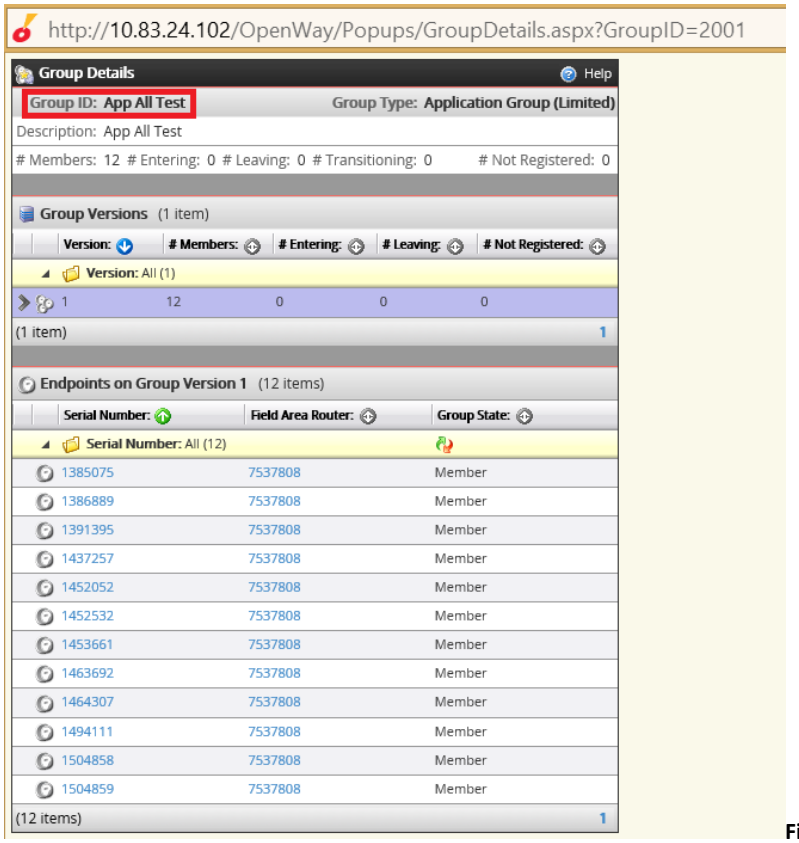


Figure 88: App All Test

2. Confirmed the Itron OpenWay Configuration is valid and that the configuration for "Automated Missed Read Time" is set to 120 hours which will allow the CE to only go back 5 days prior for gap-filling. Note that the maximum allowed for this setting is 720 hours or up to 30 days. For purposes of this test, we will only go back 5 days.

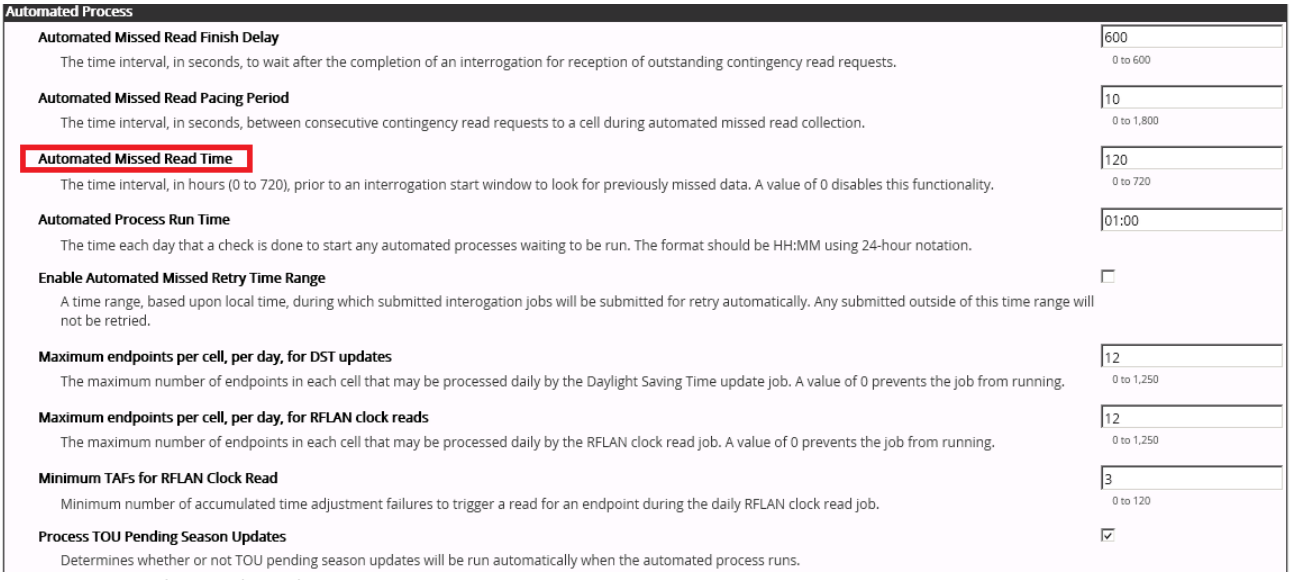


Figure 89: Automated Missed Read Time

3. Confirmed Test meters are reading prior to power down

4. Run the interrogations at regularly scheduled intervals (3 x a day) to be consistent with what we have in production
5. Verified in the MDM data is received for the meters that responded and data is missing for the meters that did not respond
6. Wait 1 entire Interrogation before analyzing the next interrogation for gap fill features
7. Validated that Contingency Read requests were executed against the meters with missing data from the prior reading
8. Manually powered down a few meters over a weekend period to produce missed reads
9. Continued to interrogate these powered down meters
10. Restored power to these powered down meters
11. Confirmed that Contingency Read requests were executed against the meters with missing data from the prior reading and that the missing reads were retrieved and stored in MDM

Detail Results

4.1. Validate that Itron CE can only go back up to 5 days to retrieve gap fill data as per the test configuration setting of 120 hours or 5 days maximum set

Steps:

1) Powered down all 12 test meters and left it on down state for 3 days
2) While meters were powered down, had MDM run the 3x day interrogation job continuously for 3 days to request data with expected results of no read
3) After 5 days, powered up all 12 test meters
4) Resume the MDM reading on those 12 meters and validate that when the meters responded, it did not request the contingency ready for anything 5 days prior.

Result: Passed

(Note: Referred to 1/20/2016 8:07 am & 1/20/2016 4:07 pm test results which shows that for any missed reads, Itron CE did go back and requested contingency reads to pick up the missed failed reads. However, for anything beyond 5 days, Itron CE did not request the contingency reads.

4.2. Validate that Itron CE successfully gap fill missing reads from a prior interrogation period

Steps:

1) As of 1/22 @ 2:10 pm, powered down a few selected meters (1385075, 1391395, 1494111, 1504858, 1504859)
2) Continue to run the interrogation jobs through MDM 3x day continuously
3) Confirmed that all these powered down meters failed to respond as of 1/22/2016 4:07 pm job. Refer to test results in Excel table below for more

details. Below are screenshots from Itron CE showing that once these meters were powered down, they stop responding

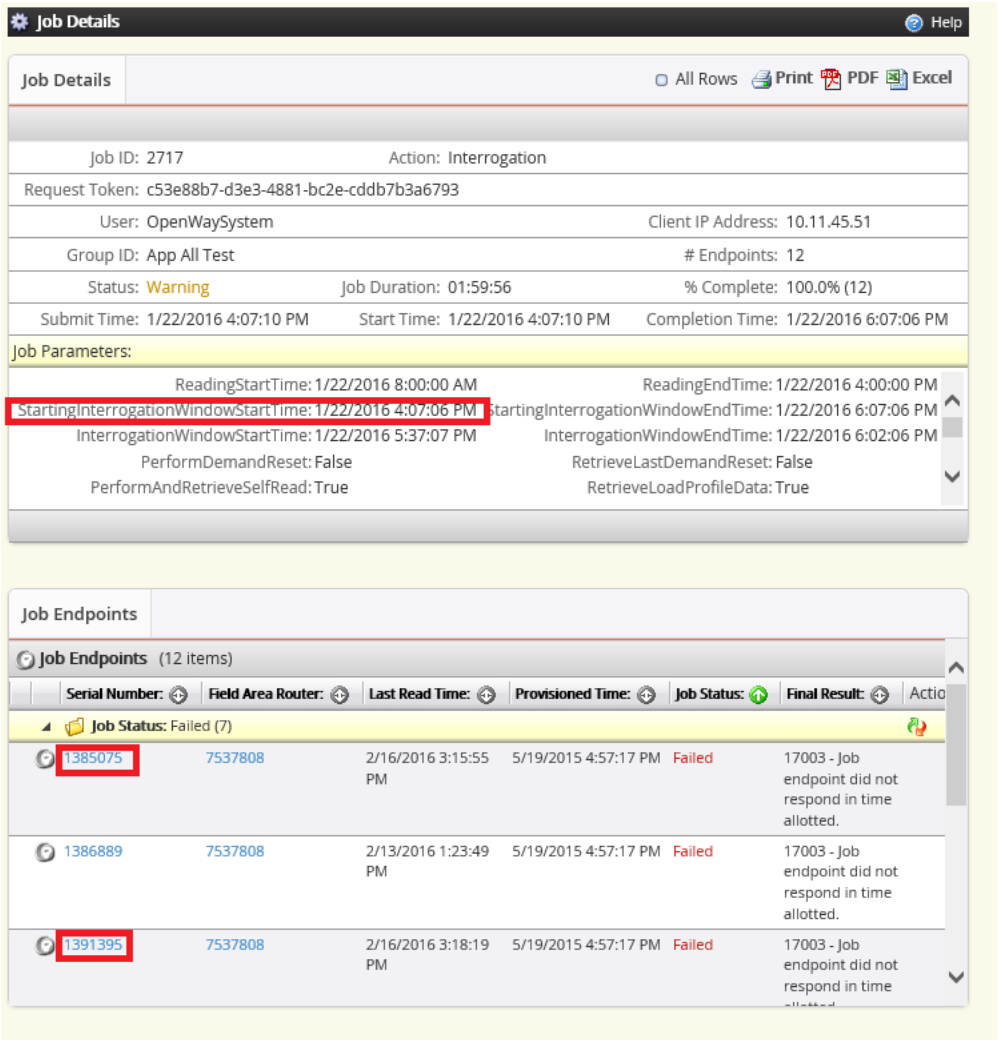


Figure 90: Failed job status

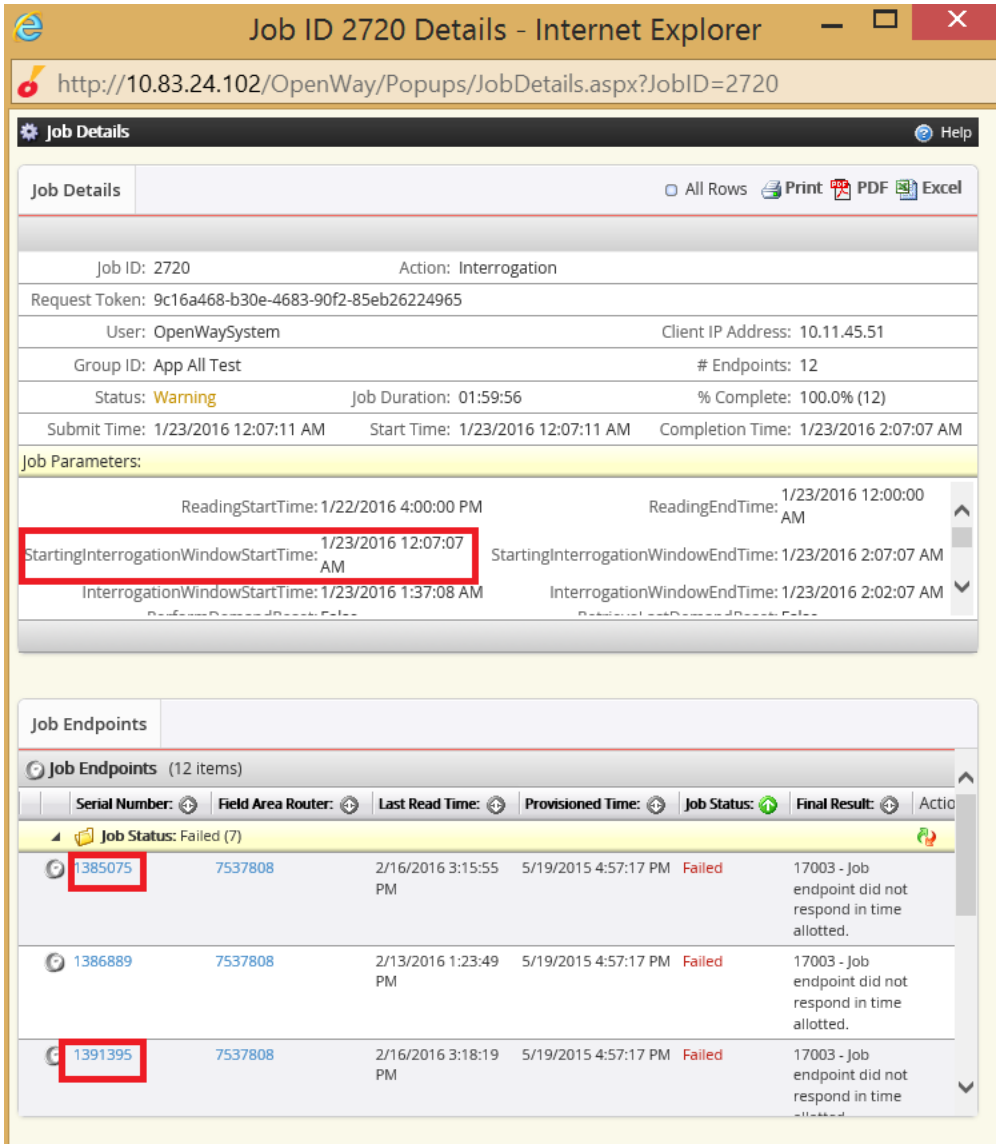


Figure 91: Interrogation Window

4) Powered up the selected meters (1385075, 1391395, 1494111, 1504858, 1504859) as of 1/25/2016 @ 8:57 am while the regular interrogation was running.
5) Confirmed in CE if any of the powered up meters responded to the 1/25/2016 @ 8:07 am interrogation & document the results.

   2 of the previous powered down meters (1385075, 1391395) responded. Refer to Iron CE screenshot below.

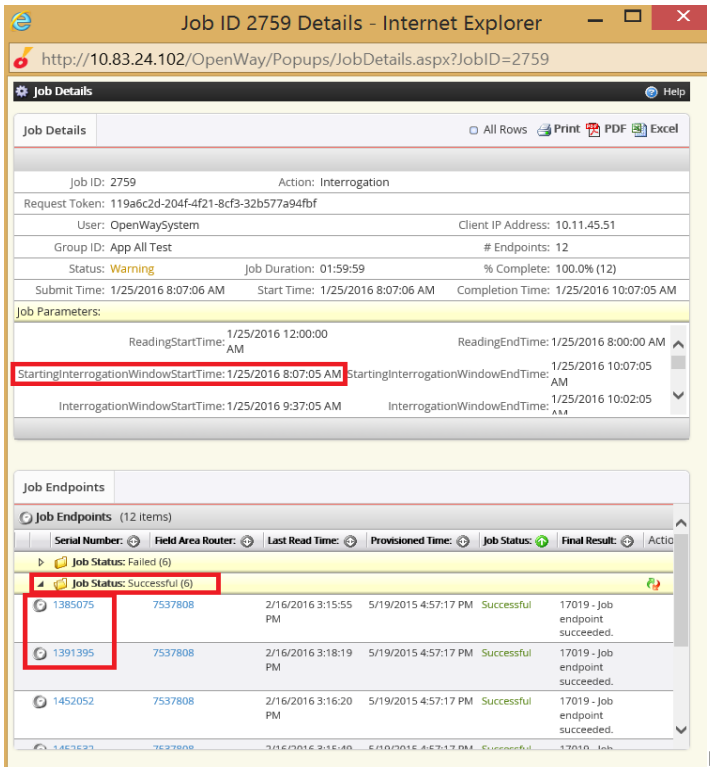


Figure 92: Success

6) Validate in MDM that readings were received for this interrogation period of 1/25/2016 12 am – 1/25/2016 8 am for meter# 01385075 & #1391395

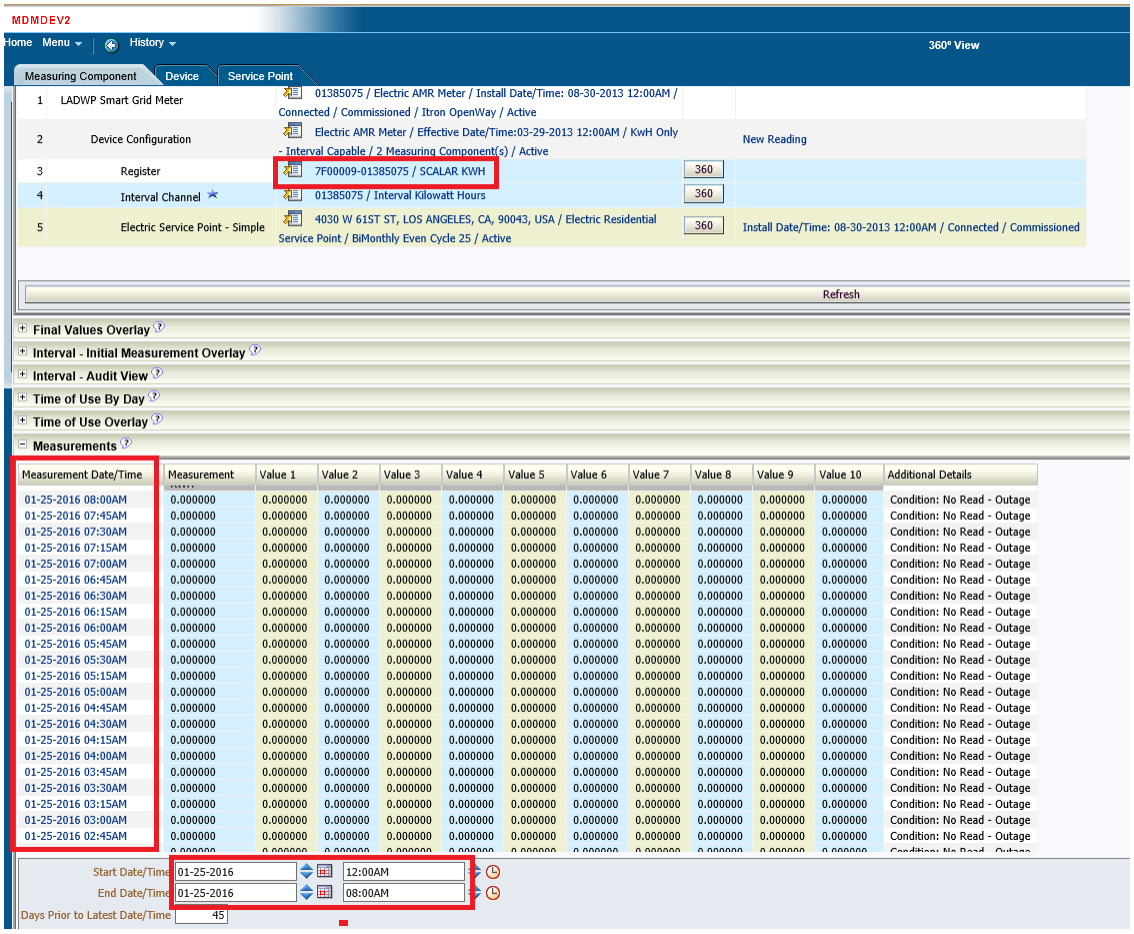


Figure 93: MDM Register

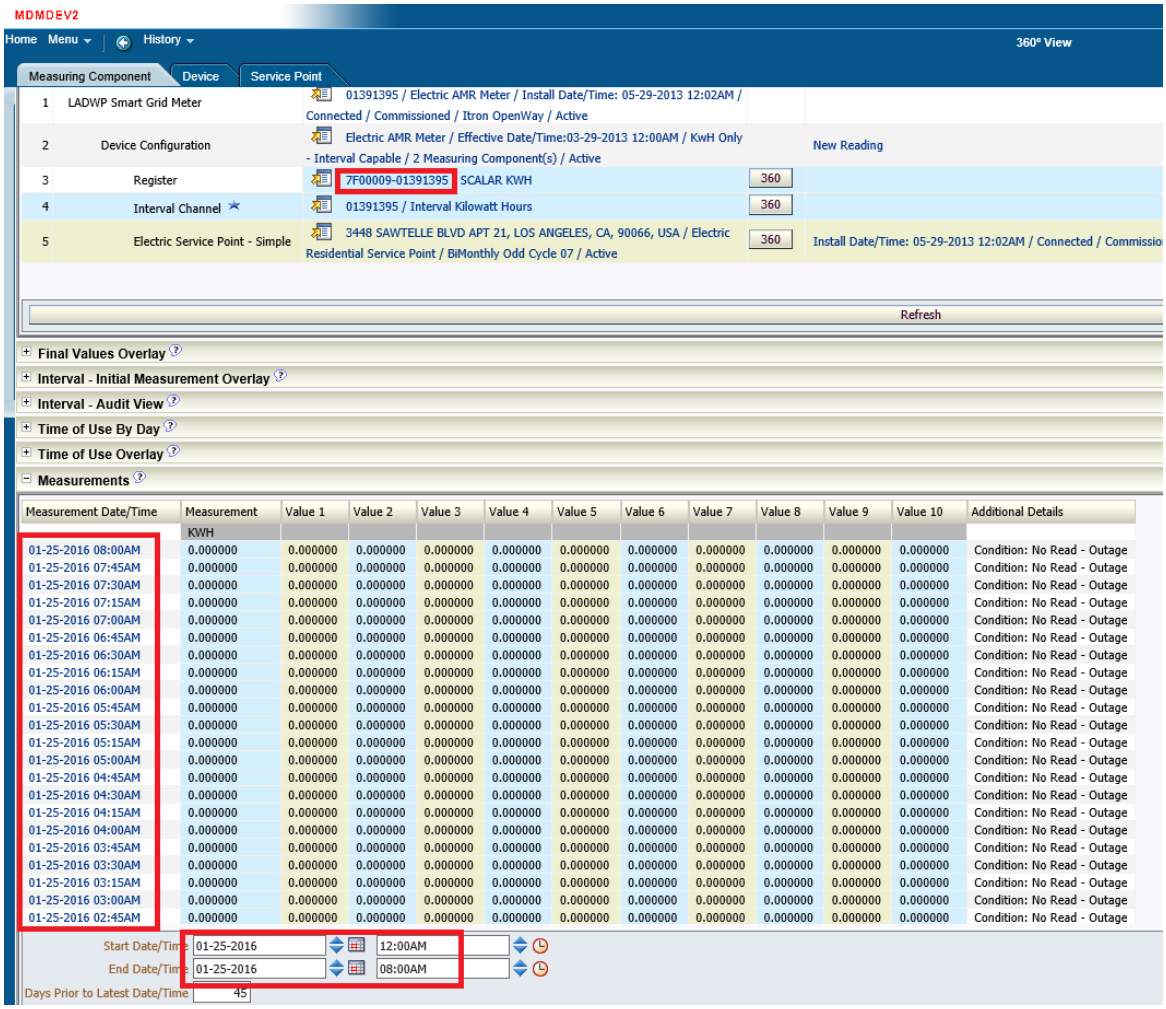


Figure 94: MDM Measurement date/Time

7) Validate that Itron CE also did gap fill contingency read to obtain data for prior missing reading of 1/22/2016 8 am – 1/25/2016 12 am.

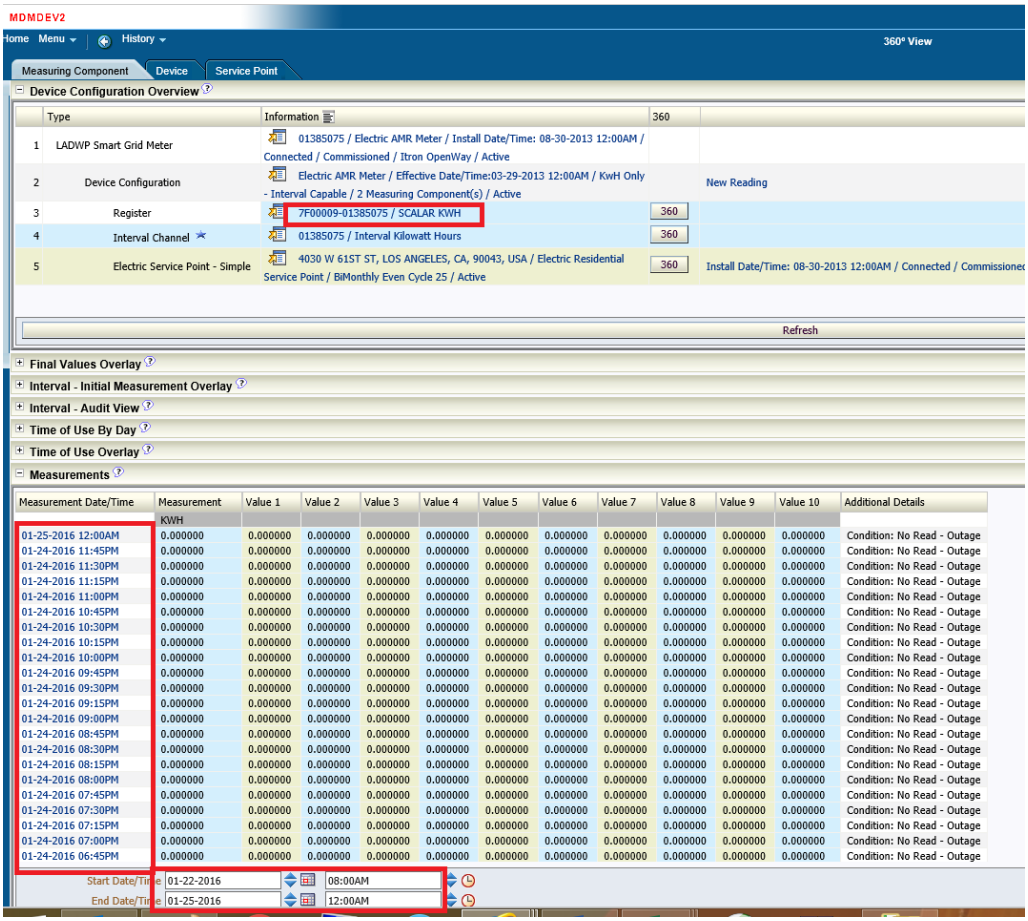


Figure 95: Validate Gap fill contingency read in MDM

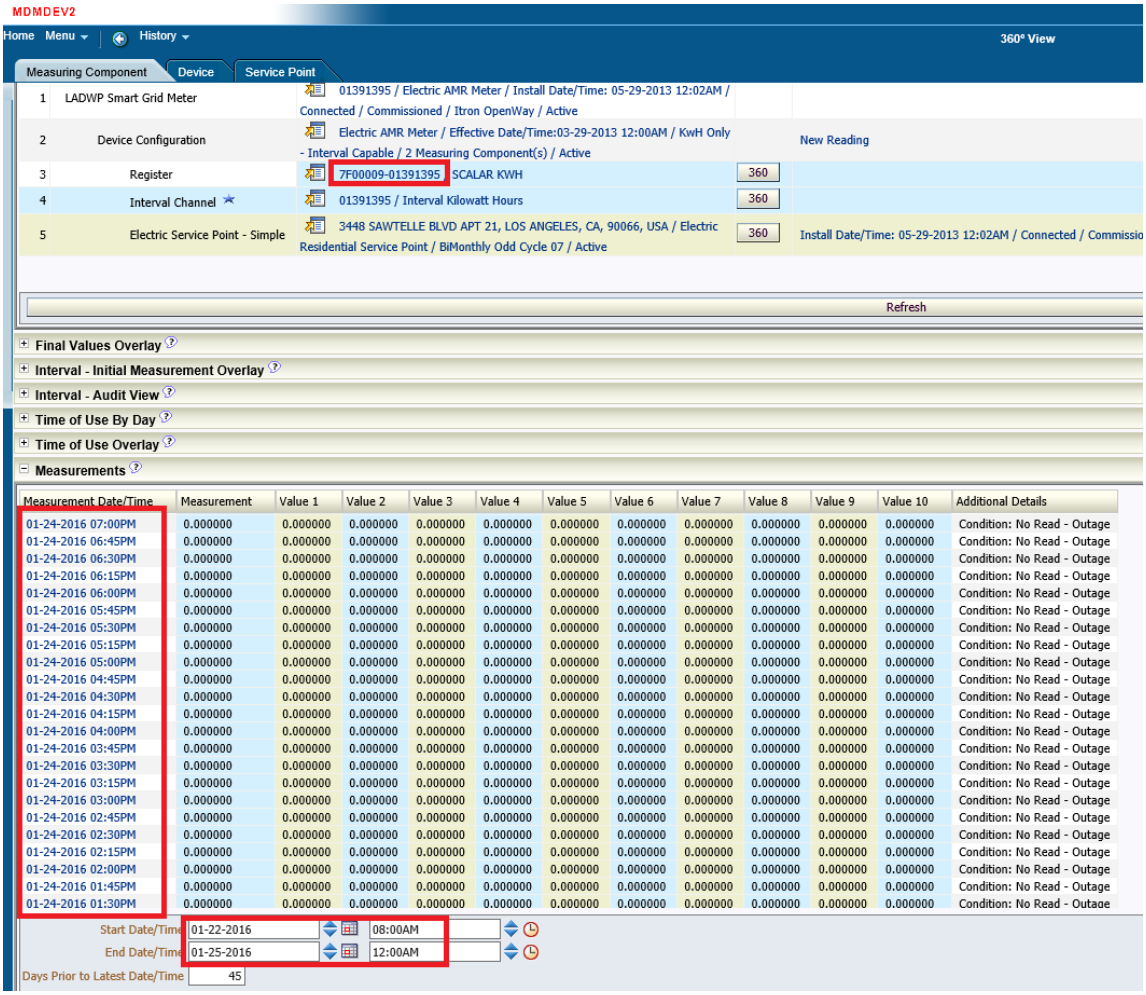
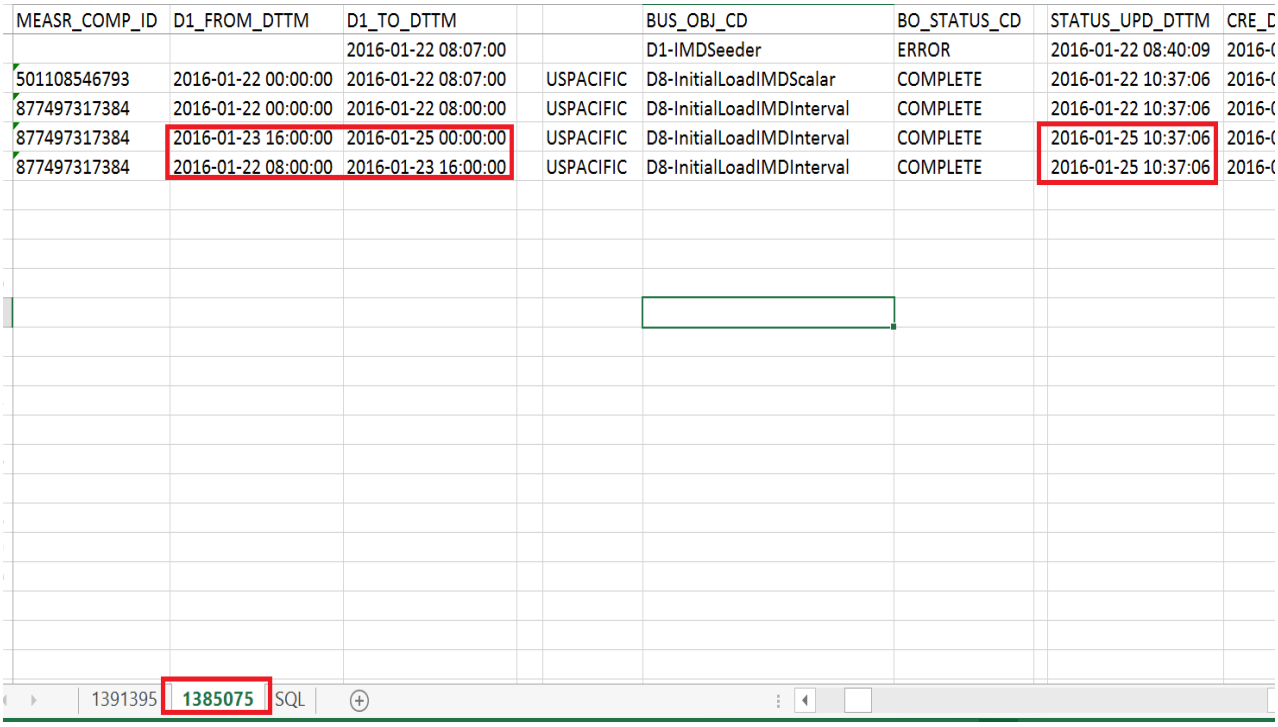


Figure 96: Verified the date MDM received the missing gap fill periods

8) Ran a query in MDMDev2 on the two meters and verified the date MDM received the missing gap fill periods of 1/22/2016 8 am – 1/25/2016 12 am was after the 1/25/2016 8 am interrogation. The reports confirmed that the reads were not received until 1/25/2016 at 9:52 & 9:53 am as expected.

INIT_MSRMT_DATA_ID	MEASR_COMP_ID	D1_FROM_DTTM	D1_TO_DTTM			BUS_OBJ_CD	BO_STATUS_CD	STATUS_UPD_DTTM	CRE_DTTM	VERSION	IMD_EXT_ID
28950901224305			2016-01-22 08:07:00			D1-IMDSeeder	ERROR	2016-01-22 08:40:09	2016-01-22 08:40:09	4	da_14185511.xml-2016-01-22-08-40-09-231
50191081079795	501108546793	2016-01-22 00:00:00	2016-01-22 08:07:00		USPACIFIC	D8-InitialLoadIMDScalar	COMPLETE	2016-01-22 10:37:06	2016-01-22 08:40:09	8	da_14185511.xml-2016-01-22-08-40-09-231
87740574471130	877497317384	2016-01-22 00:00:00	2016-01-22 08:00:00		USPACIFIC	D8-InitialLoadIMDInterval	COMPLETE	2016-01-22 10:37:06	2016-01-22 08:40:09	10	da_14185511.xml-2016-01-22-08-40-09-231
87752345931276	877497317384	2016-01-23 16:00:00	2016-01-25 00:00:00		USPACIFIC	D8-InitialLoadIMDInterval	COMPLETE	2016-01-25 10:37:06	2016-01-25 09:52:55	10	da_14185568.xml-2016-01-25-09-52-55-605
87749530478068	877497317384	2016-01-22 08:00:00	2016-01-23 16:00:00		USPACIFIC	D8-InitialLoadIMDInterval	COMPLETE	2016-01-25 10:37:06	2016-01-25 09:53:30	10	da_14185569.xml-2016-01-25-09-53-30-295

Figure 97: Output of query



MEASR_COMP_ID	D1_FROM_DTTM	D1_TO_DTTM		BUS_OBJ_CD	BO_STATUS_CD	STATUS_UPD_DTTM	CRE_D
		2016-01-22 08:07:00		D1-IMDSeeder	ERROR	2016-01-22 08:40:09	2016-(
501108546793	2016-01-22 00:00:00	2016-01-22 08:07:00	USPACIFIC	D8-InitialLoadIMDScalar	COMPLETE	2016-01-22 10:37:06	2016-(
877497317384	2016-01-22 00:00:00	2016-01-22 08:00:00	USPACIFIC	D8-InitialLoadIMDInterval	COMPLETE	2016-01-22 10:37:06	2016-(
877497317384	2016-01-23 16:00:00	2016-01-25 00:00:00	USPACIFIC	D8-InitialLoadIMDInterval	COMPLETE	2016-01-25 10:37:06	2016-(
877497317384	2016-01-22 08:00:00	2016-01-23 16:00:00	USPACIFIC	D8-InitialLoadIMDInterval	COMPLETE	2016-01-25 10:37:06	2016-(

Figure 98: Verify read time

9) Additional detailed test results and analysis are provided below:

Date	Time	Result	Expected Result	Result
1/13/2016	12:07: AM	Failed - All 12 meters	No response	Expected all meters to fail to read since they were all powered down and not on socket. This is a negative test
1/13/2016	8:07 AM	Failed - All 12 meters	No response	Expected all meters to fail to read since they were all powered down and not on socket. This is a negative test

1/13/2016	4:07 PM	Failed - All 12 meters	No response	Expected all meters to fail to read since they were all powered down and not on socket. This is a negative test
1/14/2016	12:07: AM	Failed - All 12 meters	No response	Expected all meters to fail to read since they were all powered down and not on socket. This is a negative test
1/14/2016	8:07 AM	Failed - All 12 meters	No response	Expected all meters to fail to read since they were all powered down and not on socket. This is a negative test
1/14/2016	4:07 PM	Failed - All 12 meters	No response	Expected all meters to fail to read since they were all powered down and not on socket. This is a negative test
1/15/2016	12:07: AM	Failed - All 12 meters	No response	Expected all meters to fail to read since they were all powered down and not on socket. This is a negative test

1/15/2016	8:07 AM	Failed - All 12 meters	No response	Expected all meters to fail to read since they were all powered down and not on socket. This is a negative test
1/20/2016	8:07 AM	4 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395	All new meter that responded should have reading to include missing readings prior to 1/20/2016 - 12 am	Initial test to confirm that the Itron CE has capability to only go back up to 5 days prior to retrieve data. All 12 meters were powered on and only 4 meters that responded have data logged as earliest as 1/20/16 @ 7:15 am (off by 1 hour - should be 8:15 am). There is no gap fill data for all the failed reads prior because the last failed read request was on 1/15/2016 at 8:07 am.

		1463692 1494111 1504858 1504859		
1/20/2016	########	7 meters responded	All new meter that responded should have reading to include missing readings prior to 1/20/2016 - 8 am	Meter# 1386889 - 1st logged reading is from 1/20/16 @ 7:15 am (off by 1 hour - should be 8:15 am). No prior failed reading captured.
		1385075		Meter# 1391395 - 1st logged reading is from 1/20/16 @ 7:15 am (off by 1 hour - should be 8:15 am). No prior failed reading captured.
		1452532		Meter# 1452052 - 1st logged reading is from 1/20/16 @ 7:15 am (off by 1 hour - should be 8:15 am). No prior failed reading captured.
		1453661 1464307		
		1386889 - New		Note: Seems MDM is off by 1 hour due to daylight savings.
		1391395 - New		

		1452052 - New		
1/21/2016	12:07: AM	9 meters responded 1437257- New from Previous 1452052	All new meter that responded should have reading to include missing readings prior to 1/21/2016 - 4 PM	Meter# 1437257 - 1st logged reading is from 1/20/16 @ 7:15 am (off by 1 hour - should be 8:15 am). Gap fill retrieved the missed reading from only from one prior read of 1/20/2016 8:00 am - 4:00 pm. Did not read the other missed period due to 5 day max back retrieval period. Meter# 1437257 - 1st logged reading is from 1/20/16 @ 7:15 am (off by 1 hour - should be 8:15 am). Gap fill retrieved the missed reading from only from one prior read of 1/20/2016 8:00 am - 4:00 pm. Did not read the other missed period due to 5 day max back retrieval period.

		1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111-New from Previous 1504858 1504859		
1/21/2016	8:07 AM	8 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 - didn't respond from previous 1386889 1391395 1463692 1494111 1504858 1504859		
1/21/2016	4:07 PM	9 meters responded 1437257 1452052 1452532	Expect meter 1385075 to have reading to include missing readings prior to 1/21/2016	Meter# 1385075 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/21/2016 (12 am - 8 am)

		1453661 1464307 1385075 - New from previous 1386889 1391395 1463692 1494111 1504858 1504859	- 8 AM	
1/22/2016	12:07: AM	8 meters responded 1437257 - did not respond from previous 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	
1/22/2016	8:07 AM	9 meters responded	Expect meter 1437257 to have reading to include	Meter# 1437257 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/21/2016 (4 pm - 12 am)

		1437257- new from previous 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	missing readings for 1/21/2016 from 4 pm - 12 am	
1/22/2016	4:07 PM	5 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 - did not respond from previous 1386889 - did not respond from previous	N/A	As of 2:10 pm today (Friday, 1/22), the following meters are shut down: 1385075, 1391395, 1494111, 1504858, 1504859,

		1391395 - did not respond from previous 1463692 1494111 - did not respond from previous 1504858 1504859		
1/23/2016	12:07: AM	5 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/23/2016	8:07 AM	5 meters responded 1437257 1452052 1452532	Expect meter 1386889 to have reading to include missing readings	Meter# 1386889 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/22/2016 8 am - 1/23/2016 12 am

		1453661 - did not respond from previous 1464307 1385075 1386889 - new from previous 1391395 1463692 1494111 1504858 1504859	for 1/22/2016 8 am - 1/23/2016 12 am	
1/24/2016	4:07 PM	5 meters responded 1437257 1452052 1452532 1453661 - new from previous 1464307 1385075 1386889 - did not respond from previous 1391395 1463692 1494111 1504858 1504859	Expect meter 1453661 to have reading to include missing readings for 1/23/2016 12 am - 1/23/2016 8 am	Meter# 1453661 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/23/2016 12 am - 1/23/2016 8 am

1/24/2016	12:07: AM	5 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/24/2016	8:07 AM	5 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/24/2016	4:07 PM	5 meters responded 1437257 1452052 1452532 1453661 1464307	N/A	N/A

		1385075 1386889 1391395 1463692 1494111 1504858 1504859		
1/25/2016	12:07: AM	5 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/25/2016	8:07 AM	6 meters responded 1437257- didn't respond from previous 1452052 1452532	Expect meter 1391395 & 1385075 to have reading to include missing readings for 1/22/2016 8 am - 1/25/2016 12 am	As of 1/25/2016 @ 8:57 am, all prior meters that were powered down (1385075, 1391395, 1494111, 1504858, 1504859) were powered back up. Meter# 1391395 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/22/2016 8 am - 1/25/2016 12 am

		1453661 1464307 1385075 - new from previous 1386889 1391395- new from previous 1463692 1494111 1504858 1504859		
1/25/2016	4:07 PM	9 meters responded	Expect meter 1437257 to have reading to include missing readings for 1/25/2016 12 am - 1/25/2016 8 am	Meter# 1437257 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/25/2016 12 am - 1/25/2016 8 am

		1437257-new from previous	Expect meter 1386889 to have reading to include missing readings for 1/24/2016 8 am - 1/25/2016 8 am	Meter# 1386889 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/24/2016 8 am - 1/25/2016 8 am
		1452052	Expect meter 1494111 to have reading to include missing readings for 1/22/2016 8 am - 1/25/2016 8 am	Meter# 1494111 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/22/2016 8 am - 1/25/2016 8 am
		1452532		
		1453661		
		1464307		
		1385075		
		1386889 - new from previous		
		1391395		
		1463692		
		1494111-new from previous		
		1504858		

		1504859		
1/26/2016	12:07: AM	9 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/26/2016	8:07 AM	9 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/26/2016	4:07 PM	8 meters responded 1437257 1452052 1452532 1453661	N/A	N/A

		1464307 1385075 1386889 1391395 1463692 1494111-did not respond from previous 1504858 1504859		
1/27/2016	12:07: AM	9 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111-new from previous 1504858 1504859	Expect meter 1494111 to have reading to include missing readings for 1/26/2016 8 am - 1/26/2016 4 pm	Meter# 1494111 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/26/2016 8 am - 1/26/2016 4 pm
1/27/2016	8:07 AM	9 meters responded 1437257 1452052 1452532 1453661	N/A	N/A

		1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859		
1/27/2016	4:07 PM	8 meters responded 1437257 1452052 1452532 1453661 1464307 - did not respond from previous 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/28/2016	12:07: AM	9 meters responded 1437257 1452052 1452532 1453661	Expect meter 1464307 to have reading to include missing readings for 1/27/2016 8 am - 1/27/2016	Meter# 1464307 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/27/2016 8 am - 1/27/2016 4 pm

		1464307 - new from previous 1385075 1386889 1391395 1463692 1494111 1504858 1504859	4 pm	
1/28/2016	8:07 AM	7 meters responded 1437257 - did not respond from previous 1452052 1452532 1453661 1464307 1385075 1386889 - did not respond from previous 1391395 1463692 1494111 1504858 1504859	N/A	N/A

1/28/2016	4:07 PM	8 meters responded 1437257 - new from previous 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	Expect meter 1437257 to have reading to include missing readings for 1/28/2016 12 am - 1/28/2016 8 am	Meter# 1437257 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/28/2016 12 am - 1/28/2016 8 am
1/29/2016	12:07: AM	8 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/29/2016	8:07 AM	6 meters responded	Expect meter 1386889 to have	Meter# 1386889 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/29/2016 12

		1437257 1452052 - did not respond from previous 1452532 1453661 1464307 1385075 - did not respond from previous 1386889 - new from previous 1391395 1463692 1494111 - did not respond from previous 1504858 1504859	reading to include missing readings for 1/28/2016 12 am - 1/29/2016 12 am	am - 1/29/2016 8 am

1/29/2016	4:07 PM	8 meters responded	Expect meter 1452052 to have reading to include missing readings for 1/29/2016 12 am - 1/29/2016 8 am	Meter# 1452052 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/29/2016 12 am - 1/29/2016 8 am
		1437257	Expect meter 1385075 to have reading to include missing readings for 1/29/2016 12 am - 1/29/2016 8 am	

		1452052 - new from previous	Expect meter 1494111 to have reading to include missing readings for 1/29/2016 12 am - 1/29/2016 8 am	Meter# 1385075 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/29/2016 12 am - 1/29/2016 8 am
		1452532		
		1453661		Meter# 1494111 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/29/2016 12 am - 1/29/2016 8 am
		1464307		
		1385075 - new from previous		
		1386889 - did not respond from previous		
		1391395		
		1463692		

		1494111 - new from previous 1504858 1504859		
1/30/2016	12:07: AM	8 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/30/2016	8:07 AM	9 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 - new from previous 1391395 1463692 1494111 1504858	Expect meter 1386889 to have reading to include missing readings for 1/29/2016 8 am - 1/30/2016 12 am	Meter#1386889 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/29/2016 8 am - 1/30/2016 12 am

		1504859		
1/30/2016	4:07 PM	7 meters responded 1437257 1452052 - did not respond from previous 1452532 1453661 1464307 1385075 1386889 - did not respond from previous 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/31/2016	12:07: AM	7 meters responded 1437257 - did not respond from previous 1452052 - new from previous 1452532	Expect meter 1452052 to have reading to include missing readings for 1/30/2016 8 am - 1/30/2016 4 pm	Meter#1452052 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/30/2016 8 am - 1/30/2016 4 pm

		1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859		
1/31/2016	8:07 AM	6 meters responded 1437257 1452052 - did not respond from previous 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
1/31/2016	4:07 PM	7 meters responded 1437257 - new from previous 1452052 1452532	Expect meter 1437257 to have reading to include missing readings for 1/30/2016 4 pm - 1/31/2016 8 am	Meter#1437257 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/30/2016 4 pm - 1/31/2016 8 am

		1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859		
2/1/2016	12:07: AM	7 meters responded 1437257 1452052 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	N/A	N/A
2/1/2016	8:07 AM	6 meters responded 1437257 - did not respond from previous 1452052 - new from previous	Expect meter 1452052 to have reading to include missing readings for 1/31/2016 12 am - 2/1/2016 12 am	Meter#1452052 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 1/31/2016 12 am - 2/1/2016 12 am

		1452532- did not respond from previous 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859		
2/1/2016	4:07 PM	8 meters responded 1437257 1452052 1452532- new from prior 1453661 1464307 1385075 1386889 - new from prior 1391395 1463692 1494111 1504858 1504859	Expect meter 1452532 & 1386889 to have reading to include missing readings for 2/1/2016 12 am - 2/1/2016 8 am	Meter#1452052 & 1386889 - confirmed in MDM that data was received for this reading period but also gap fill did pick up the prior missed reading from 2/1/2016 12 am - 2/1/2016 8 am
2/2/2016	12:07: AM	8 meters responded 1437257	N/A - since same set of meters missed	

		1452052 - 1452532 1453661 1464307 1385075 1386889 1391395 1463692 1494111 1504858 1504859	prior readings	

Test Result: Passed – Itron CE has gap fill capability

Appendix E AMI Gap Fill Test

Purpose

The purpose of this document is to capture the test results of validating that Itron OpenWay Collection Engine supports a gap fill concept, called Automated Missed Read Retry for up to 30 days.

Summary

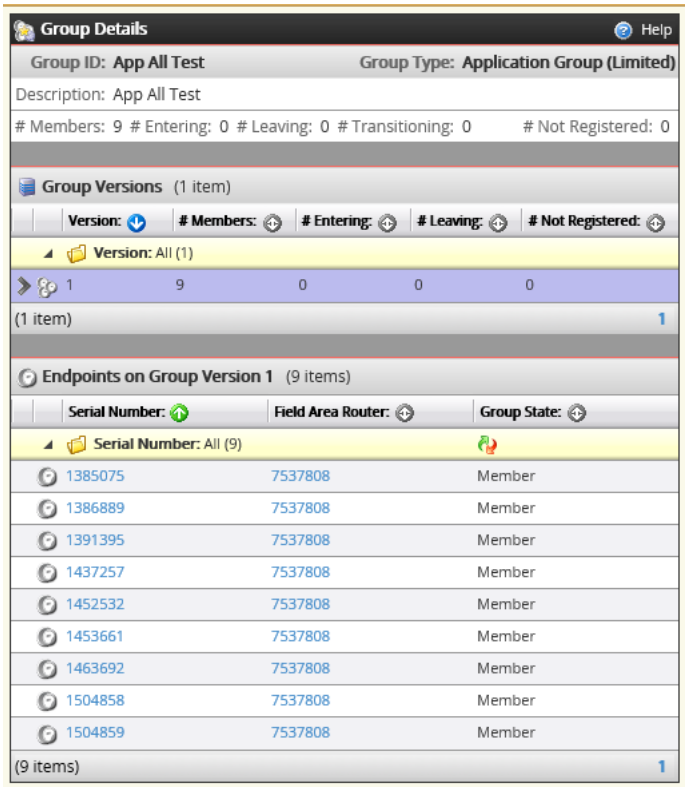
Los Angeles Department of Water and Power (LADWP) has installed 51,190 AMI meters. Using Oracle MDM, these meters are read 3 times a day at the respective time of 8:05 am, 4:05 pm, and 12:05 am. Each interrogation includes a requests for load profile, registers and meter events for the prior past 8 hours. On any given day, there is a 3-8% meter failure response rate. LADWP's goal is to achieve 100% readings for each meter to ensure billing accuracy in the near future. As such, LADWP would like to validate that Itron OpenWay Collection Engine is capable of handling gap filled reads for up to 30 days.

Itron OpenWay Collection Engine supports a gap fill concept, called Automated Missed Read Retry. If there is a missed Interrogation request, the Collection Engine will "create" a pending Contingency Read for the meter. The parameters for the Contingency Read request will be equal to the missed Interrogation request, meaning if load profile and events were requested as part of Interrogation, then load profile and events will be requested as part of Contingency Read request. The created Contingency Read request is held by the OpenWay Collection Engine until the meters respond to the current Interrogation request, if the meter does not respond to the current running Interrogation request the OpenWay Collection Engine does not submit the Contingency Read request. Currently, Itron OpenWay Collection Engine is capable of handling gap filled reads for only up to the past 30 days.

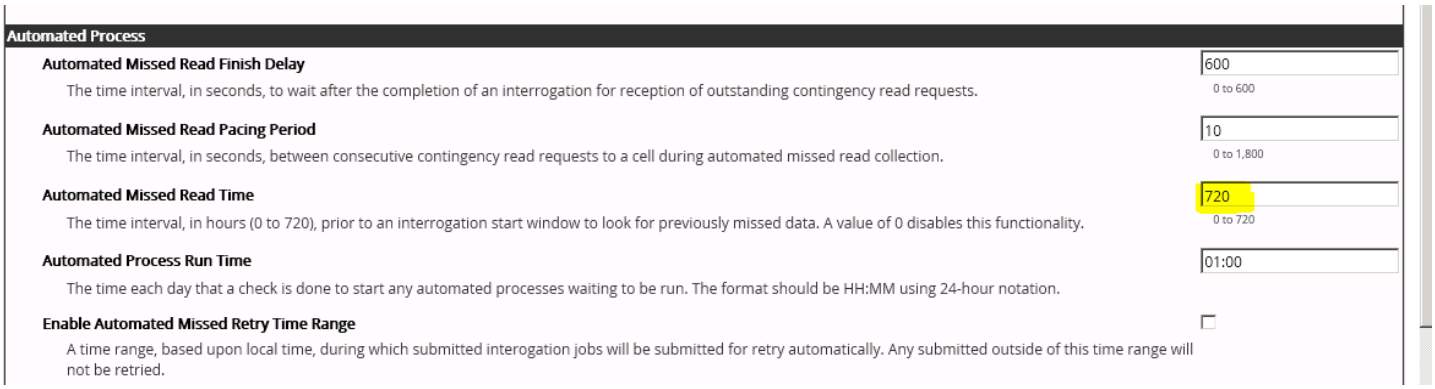
Details of the Test

The test was conducted using MDMDev2 v2.1 against the Test Collection Engine v6.6. Below are the overall high-level test steps:

1. Select "App All Test" Group in Collection Engine



2. Confirmed the Itron OpenWay Configuration is valid and that the configuration for "Automated Missed Read Time" is set to 720 hours which will allow the CE to go back 30 days prior for gap-filling. Note that the maximum hours allowed for this setting is 720 or up to 30 days.



3. Confirmed Test meters are reading prior to power down

4. Run the interrogations at regularly scheduled intervals (3 x a day) to be consistent with what we have in production

5. Verified in the MDM data is received for the meters that responded and data is missing for the meters that did not respond

6. Wait 1 entire Interrogation before analyzing the next interrogation for gap filled features

7. Validated that Contingency Read requests were executed against the meters that has missing data from the prior reading

8. Manually powered down a few meters for a period of 30 days to produce missed reads

9. Continued to interrogate these powered down meters

10. Restored power to these powered down meters

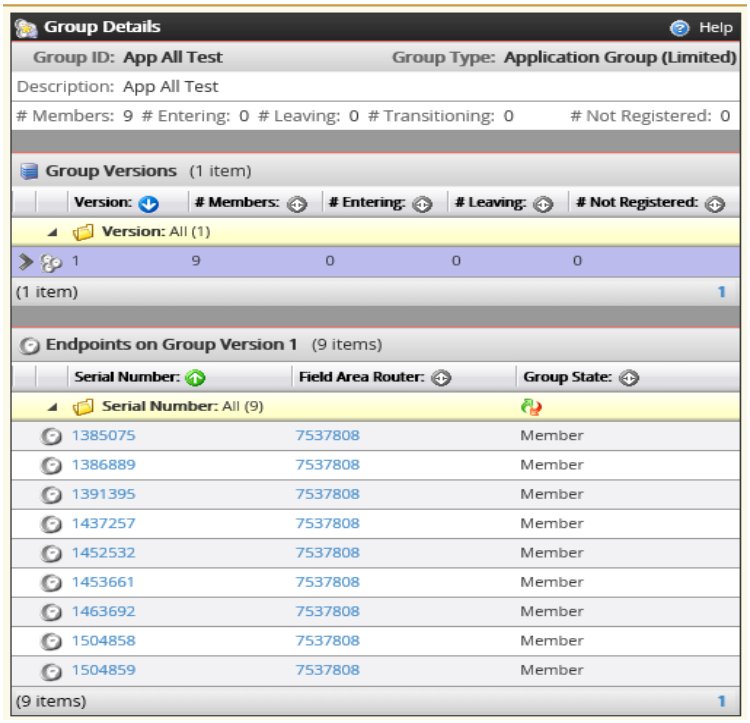
11. Confirmed that Contingency Read requests were executed against the meters that has missing data from the prior reading and that the missing reads were retrieved and stored in MDM

Detail Results

4.1. Validate that Itron CE can only go back up to 30 days to retrieve gap filled data as per the test configuration setting of 720 hours or 30 days maximum set

Steps:

1) Select a few meters from the App All Group that was communicating for this test.



Group Details — Help

Group ID: App All Test — Group Type: Application Group (Limited)

Description: App All Test

Members: 9 # Entering: 0 # Leaving: 0 # Transitioning: 0 # Not Registered: 0

Group Versions (1 item)

Version:	# Members:	# Entering:	# Leaving:	# Not Registered:
Version: All (1)				
1	9	0	0	0

(1 item) 1

Endpoints on Group Version 1 (9 items)

Serial Number:	Field Area Router:	Group State:
Serial Number: All (9)		
1385075	7537808	Member
1386889	7537808	Member
1391395	7537808	Member
1437257	7537808	Member
1452532	7537808	Member
1453661	7537808	Member
1463692	7537808	Member
1504858	7537808	Member
1504859	7537808	Member

(9 items) 1

2) Powered down all 8 Test meters that was communicating with exception of one meter (1453611) and left it on down state for 30 days.

From: Taijan, Afshin [mailto:Afshin.Taijan.consultant@ladwp.com]
Sent: Wednesday, April 13, 2016 10:17 AM
To: Thuy-An Nguyen
Cc: Mehrkhodavandi, Houman; Peji, Annamae
Subject: RE: Plan Frequent Interrogation of Solar Meters & Gap Filled Testing Result

All mentioned meters except "1453661" are powered don as of 10AM this morning.

Best,
Afshin

3) While meters were powered down, had MDM run the 3x day interrogation job continuously for the next 30 days

4) Monitor and confirm that all the shut off meters was not communicating despite the interrogation and also confirm that the meter that was on was indeed communicating. (Per screenshot below, all meters are failing except for the 1 meter (1453661) that was not turned off.

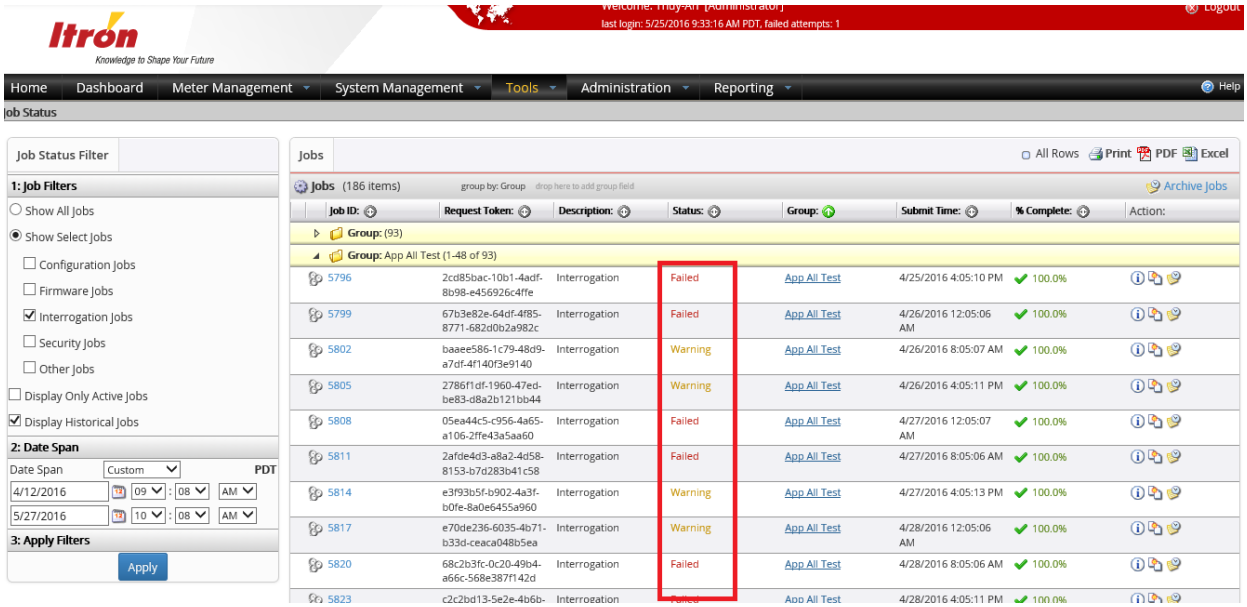


Figure 3.0 – Screenshot showing that once meters are powered down, the reads started to fail during the interrogation

5865	f56eee85-39c6-4811-b175-5b0f7adc1a12	Interrogation	Failed	App All Test	5/3/2016 8:05:06 AM	100.0%	
5868	4f8cb93c-1fe4-4ddc-9625-91bfc38ddaac	Interrogation	Failed	App All Test	5/3/2016 4:05:12 PM	100.0%	
5871	5b10ed48-0681-4e20-9afe-be4df6171ae9	Interrogation	Failed	App All Test	5/4/2016 12:05:06 AM	100.0%	
5874	39450dd6-547b-467a-8020-739d906a8f41	Interrogation	Failed	App All Test	5/4/2016 8:05:06 AM	100.0%	
5877	c9c02029-6645-41db-b2dd-0430d9bffded	Interrogation	Failed	App All Test	5/4/2016 4:05:11 PM	100.0%	
5880	ce11947e-8f8a-402e-ade0-27394d606a76	Interrogation	Failed	App All Test	5/5/2016 12:05:07 AM	100.0%	
5883	8cf80afe-564e-4d2b-a344-3cedea415759	Interrogation	Failed	App All Test	5/5/2016 8:05:06 AM	100.0%	
5886	d18ce6c5-a199-4d9d-9239-a2fcbfe5d7de	Interrogation	Failed	App All Test	5/5/2016 4:05:11 PM	100.0%	
5889	e53ed68a-ade8-4605-91ee-cbeb1a225c81	Interrogation	Failed	App All Test	5/6/2016 12:05:06 AM	100.0%	
5892	be39ea5c-26ac-4974-9c27-2071a6dfed15	Interrogation	Failed	App All Test	5/6/2016 8:05:06 AM	100.0%	
5895	5c250949-459b-417a-b5af-7161c559e0d2	Interrogation	Failed	App All Test	5/6/2016 4:05:10 PM	100.0%	
5898	9d8177d7-ee11-4769-b1e0-893de056e1fa	Interrogation	Failed	App All Test	5/7/2016 12:05:07 AM	100.0%	

Figure 3.1 – Screenshot showing that the meters continued to failed to respond to any interrogations in the next few weeks

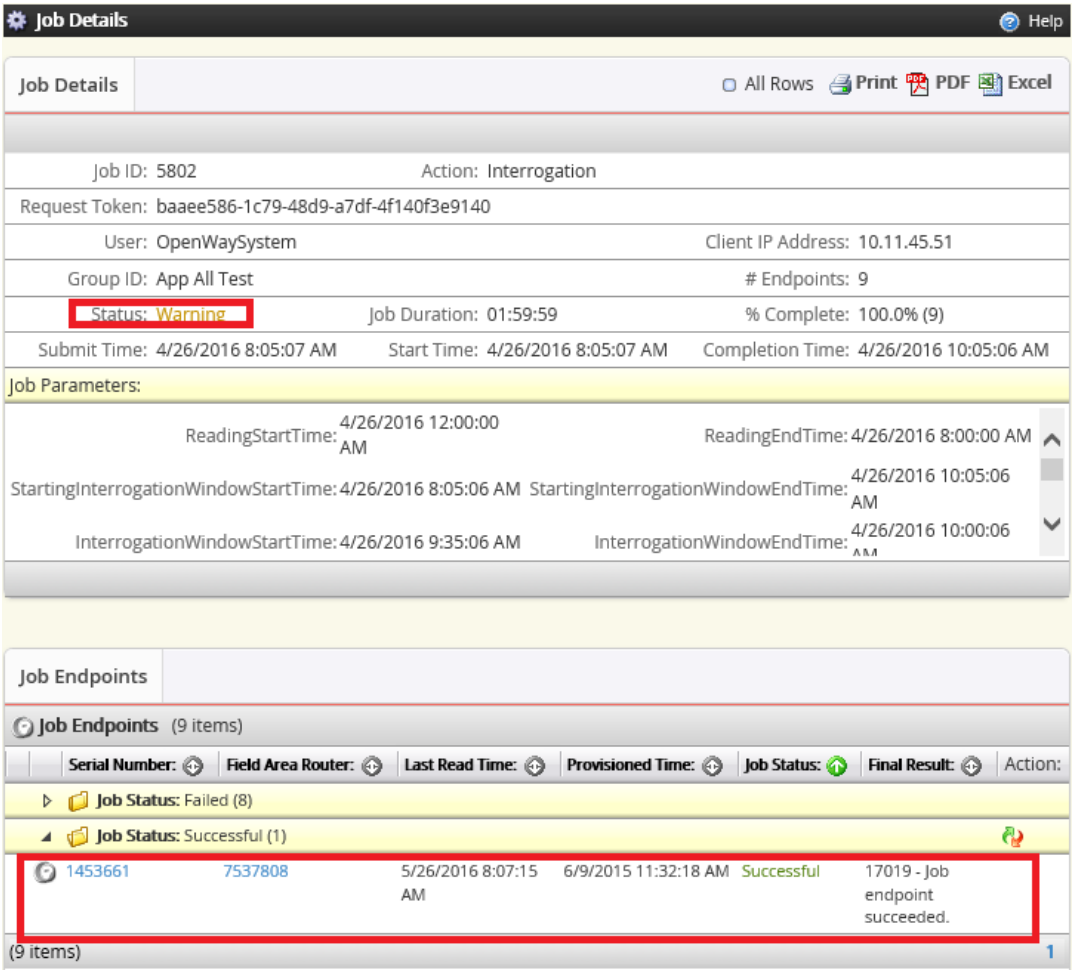


Figure 3.2 shows that the "Warning" Status is because there was one meter (meter# 1453661) that responded to the interrogation which was expected because that was the one meter that we left on)

5) After 30 days, powered up all the meters

From: Tajian, Afshin [mailto:Afshin.Tajian.consultant@ladwp.com]
Sent: Wednesday, May 18, 2016 8:27 AM
To: Thuy-An Nguyen <Thy@smartusys.com>
Subject: RE: Plan Frequent Interrogation of Solar Meters & Gap Filled Testing Result

The meters are now energized - as of 8:20am this morning.

Afshin Tajian
JFB 848
x74153

6) Monitor Itron CE on all those meters and validate that they responded to the interrogation read once powered back on 5/18/2016 @ 8:02 am

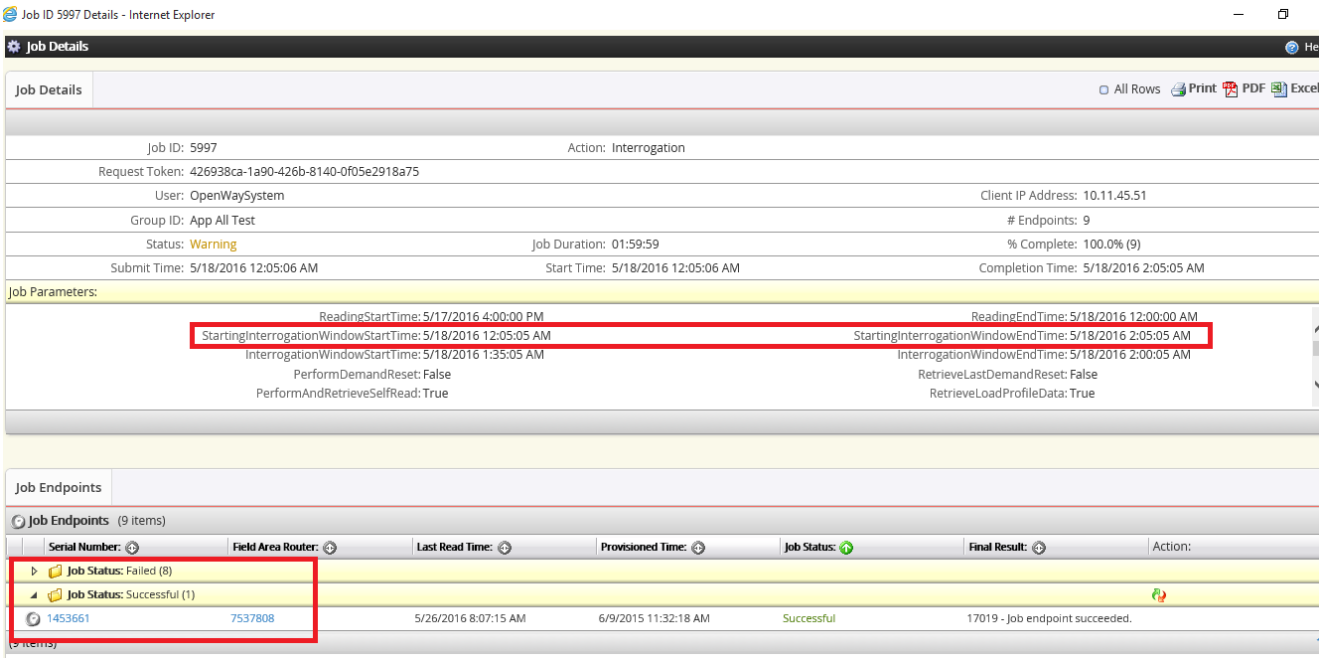


Figure 6.0 shows that last interrogation job of 5/18/2016 @ 12 am prior to the meters being turned back on continues to failed with only 1 meter responding

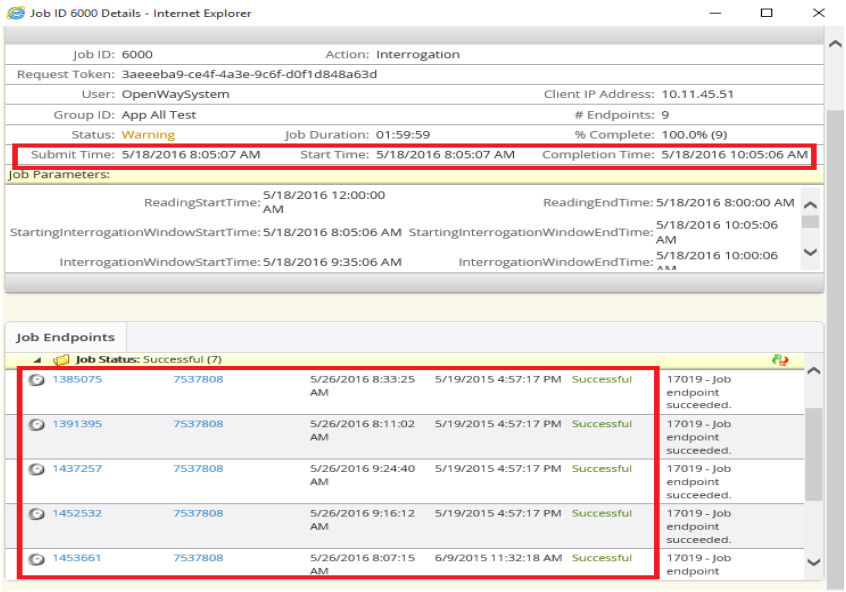


Figure 6.1 shows that 7 meters responded as soon as they were powered back on to the 5/18/2016
@ 8 am interrogation

7) Confirm in MDM that data was received for all those meters that responded

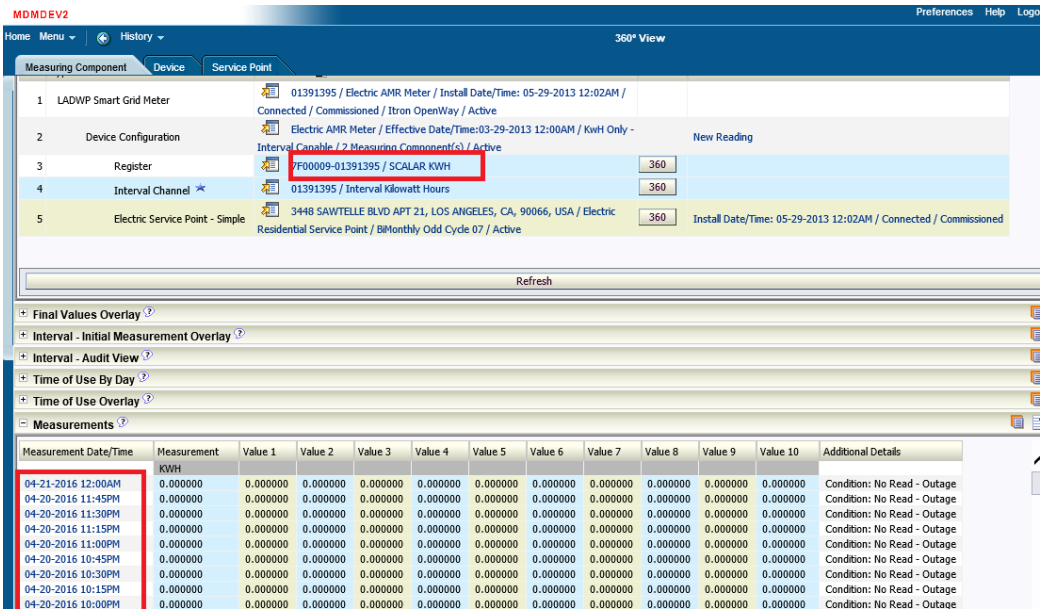
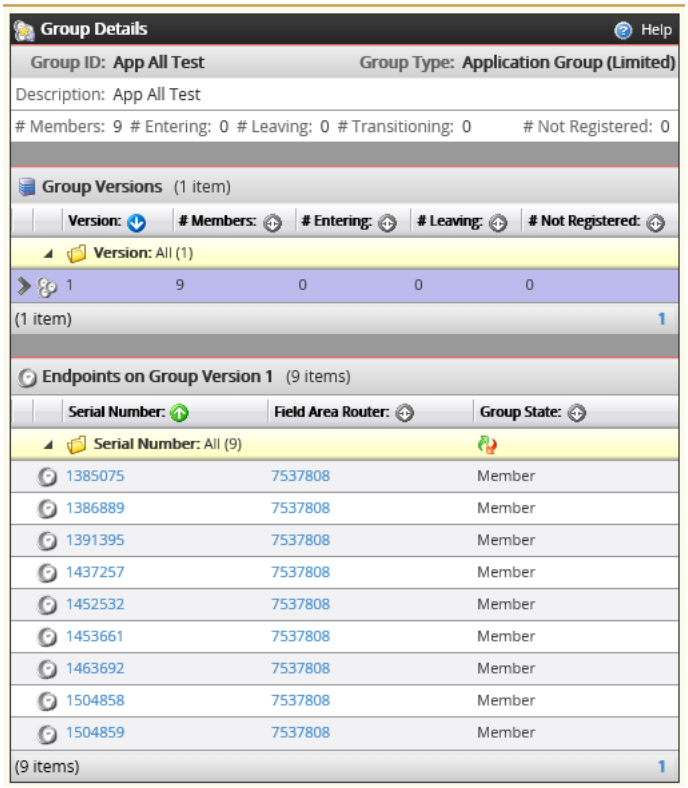


Figure 7.0 shows Meter# 01391395 having data in April when meter was shut down which proves that gap-filled work



Group Details — Help

Group ID: App All Test — Group Type: Application Group (Limited)

Description: App All Test

Members: 9 # Entering: 0 # Leaving: 0 # Transitioning: 0 # Not Registered: 0

Group Versions (1 item)

Version:	# Members:	# Entering:	# Leaving:	# Not Registered:
Version: All (1)				
1	9	0	0	0

(1 item) 1

Endpoints on Group Version 1 (9 items)

Serial Number:	Field Area Router:	Group State:
Serial Number: All (9)		
1385075	7537808	Member
1386889	7537808	Member
1391395	7537808	Member
1437257	7537808	Member
1452532	7537808	Member
1453661	7537808	Member
1463692	7537808	Member
1504858	7537808	Member
1504859	7537808	Member

(9 items) 1

Figure 7.1 shows all the 9 test meters in App Group. All 8 was turned off with exception of meter#1453661 as of 4/13 @ 10 am all the way until 5/18/2016.

TEST RESULT: Passed – Itron CE has gap filled capability for up to 30 days.

Recommendations

- We were unable to test the following scenarios

1. We were unable to test a larger sample of meters to verify if performance will be an issue or whether Itron CE will be able to scale in handling gap-filled on a larger volume of meters

- Overall it looks like Itron CE is capable of handling the basic gap-filled read for past 30 days on the selected few test meters that we conducted.

Appendix F Smart Grid LA Baseline Survey Summary Report

Smart Grid LA Baseline Survey Summary Report

Los Angeles Department of Water and Power Smart Grid Regional Demonstration Program

Customer Behavior Project

This material is based upon work supported by the Department of Energy under Award Number DE-OE0000192.

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1. Change History

a. Author(s): Nicole Sintov
b. Reviewer/Approvers: Adam Chhan

2. Executive Summary

The primary goal of this study was to assess baseline attitudes, perceptions, and behaviors related to energy management technologies among the LADWP customer base. In addition, these findings serve as a baseline against which follow-up survey data, to be collected at the end of the Operations period, will be compared. A total of 1000 LADWP customers completed surveys via structured phone interviews. The sample included 500 SGRDP customers and 500 non-SGRDP customers. Key findings and recommendations are as follows:

- Many SGRDP respondents were not aware they had a smart meter installed at their home: only 27% correctly identified having a meter installed. This suggests that the multiple direct mail materials regarding meter installation were not opened, attended to, or perhaps forgotten about by participants.
- The sample also reported low levels of knowledge related to smart meters. Nonetheless, respondents reported neutral to favorable opinions related to smart meters.
- More than two-thirds of respondents were open to participating TOU pricing plans and Save Power Events.
- In terms of preferences for monitoring home energy usage, no major differences were observed, but in-home displays were slightly preferred.

- Participants tended to overestimate amount of energy they could save if they made an effort (36%). If participants set goals that cannot be achieved, they may become discouraged and stop trying. This finding suggests that energy awareness can be improved so participants are able to set realistic and achievable conservation goals.
- Overall, respondents believed that less than half of their neighbors were conserving energy. This suggests an opportunity to convey social norms about the energy conservation efforts of others that can motivate participants to conserve in their own homes.
- Based on perceived benefits of smart grid systems, the following benefits should be highlighted in SGRDP program messaging: environmental benefits, ability to control bill, efficiency of grid system

3. An Overview of the Demonstration

a. Smart grid capabilities and functions demonstrated

The present study demonstrated the following functions from the SOPO:

1. Demonstrate the impact of smart grid communication systems and processes on customer usage patterns.
2. Demonstrate effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns.
3. Demonstrate communication and media content on Smart Grid deployment, incorporating changes observed in awareness, attitudes, and energy use behaviors.

b. Smart grid impacts and benefits demonstrated

Electric power interruptions are associated with significant economic consequences, with annual losses ranging from €150 among European Union businesses to $80 billion among the United States economy (Lawrence Berkeley National Laboratory, 2004) to 6-20% of commercial sales lost among African nations. Electric utilities allocate considerable resources to avoiding interruptions. Toward this end, each year utilities are investing $700 million in demand response (DR) strategies to curtail peak load as alternatives to bringing on additional generation, which is environmentally and economically costly (US Energy Information Administration, 2013).

DR forecasting models predict when, where, and how much energy will be used, but solving the key problem of *how* to ultimately reduce demand requires programs that encourage electric customers to make real-time, voluntary behavioral changes to curtail energy use during peak hours. The US Federal Energy Regulatory Commission characterizes DR as a “bottom-up process…driven by changes in customer behavior”. A number of white papers suggest that such programs, many of which offer small monetary incentives, can be effective in reducing peak demand. However, the majority of programs have not been evaluated, and methodological limitations among those that have suggest areas for improvement. Often, these tools are delivered via new technologies such as mobile phone apps, web sites, or electronic in-home displays. Understanding which technologies customers are willing to engage with, and what they prefer to engage with, is critical to shaping programs that will have positive customer uptake.

Social science approaches must be leveraged to improve these efforts. Decades of research support the effectiveness of various tools in changing end-user behaviors to ultimately reduce overall household energy use. However, the optimal tools for promoting continuous, long-term energy conservation may differ from those that can support discrete, time-delimited behavior change. Persuasive messaging can be a cost-effective, time-sensitive strategy for promoting participation in DR events. Additionally, persuasion remains one of the more complex and interesting domains within social psychological research. Understanding what motivators resonate with customers can guide program messaging and contribute to a successful rollout.

c. List of Objectives/Scope

The primary goal of this study was to assess baseline attitudes, perceptions, and behaviors related to energy management technologies among the LADWP customer base. In addition, these findings serve as a baseline against which follow-up survey data, to be collected at the end of the Operations period, will be compared. Including both SGRDP and non-SGRDP customers also enables us to explore differential rates of change among these subgroups. We hypothesize that attitudes towards energy management technologies and willingness to use these technologies will become more positive among SGRDP customers relative to non-SGRDP customers. Interacting with the program and engaging with energy data are hypothesized mediators of these changes.

d. Mapping to the SOPO & Deliverables

The following deliverables from the SOPO are presented in this report:

1. Identification of the key socio-demographic and community structure variables in the Smart Grid adoption process.
2. Identification of the key decision factors in the adoption of Smart Grid related technologies.
3. Integration of behavioral and social factors into the design and implementation of Smart Grid information architecture, data management, and cyber-security systems.
4. Delivery of comprehensive data, analysis, and models relating socio-demographic compositions and customer use types to Smart Grid technology acceptance and use patterns.
5. Periodic reports documenting the results of the demonstration.

4. Descriptions of the methodologies utilized

Method

Participants

A total of 1000 LADWP customers completed surveys via phone interviews. The sample included 500 SGRDP customers and 500 non-SGRDP customers. A phone survey company conducted the interviews by phone using a highly structured interview protocol. See Appendix A for interview questions. A total of 70,529 calls were placed. Of these, approximately 1.4% were completed interviews, 2.3% scheduled call-backs, less than 1% terminated mid-interview, and 9% declined to participate. For 7.9% of calls, the respondent was not available to participate at the time of the call, and approximately 4.2% calls reached ineligible respondents. For the remaining 75.3% of calls, no respondent answered the phone. Approximately 7% of calls were conducted in Spanish.

Eligibility. Individuals could participate in the study if they were adult LADWP customers. Eligibility was determined by survey responses.

The sample roughly matched demographic and housing characteristics for Los Angeles County based on US Census data except for educational attainment and ethnic distribution. The sample included a higher percentage of high school and college graduates relative to Los Angeles. Additionally, the sample under-represented Latinos relative to Los Angeles. See tables 1 and 2 below for details. A total of 87.2% of participants agreed to participate in a follow-up survey.

Table 1. Demographic characteristics of sample relative to Los Angeles County.

Characteristic	Sample	SGRDP	Non-SGRDP	Los Angeles County
Gender (% female)	55.7	54.0	57.4	50.3

Mean age [a] (SD)	47.7 (18.0)	49.0 (18.66)	46.4 (17.32)	
Ethnicity				
African American	14.6	16.3	12.8	9.6
Asian / Asian American	8.2	7.9	8.4	11.1
Caucasian	43.2	44.5	41.9	38.7
Latino	22.4	19.8	25.1	48.5
Native American / Pacific Islander	1.6	1.5	1.7	0.8
Multiracial	4.1	4.0	4.2	4.6
Other	6.0	6.1	5.9	--
Language spoken at home				
English	81.2	82.2	79.6	60.2
Spanish	12.6	10.6	14.6	--
Other language	4.2	7.2	5.8	--
Educational Attainment (>=25 yrs)				
Less than High School	6.6	5.7	7.6	25.8
High school diploma	12.0	11.6	12.6	19.3
Technical/trade school	1.5	1.7	1.3	--
Some college / Associate's degree	25.4	26.4	24.5	24.1
4-year college degree	28.9	28.3	29.5	20.4
Graduate / professional degree	25.4	26.4	24.5	10.4
HS degree or higher	93.2	94.3	92.4	74.2
Bach or higher	54.3	54.7	54.0	30.8
Political Affiliation				--
Liberal	53.1	52.7	53.4	
Moderate	20.4	20.4	20.3	
Conservative	26.6	26.9	26.3	
Annual household income				Median household income: $49,745
<$25,000	27.1	27.5	26.7	
$25,001-$50,000	25.1	26.6	23.7	
$50,001-$75,000	16.8	16.8	16.8	
$75,001-$100,000	11.2	11.4	11.1	
>$100,000	19.7	17.7	21.7	
Marital Status [b]				--
Never married	37.4	32.2	39.6	
Currently married	38.7	40.2	37.3	
Domestic Partnership	3.0	1.2	4.8	
Separated	17.03	20.1	14.0	
No longer married	3.8	3.3	4.4	

[a] t=-2.28, p<.03

[b] Never married vs. ever married chi square = 6.30, p<.02

Table 2. Household characteristics of sample relative to Los Angeles County.

	Sample	SGRDP	Non-SGRDP	Los Angeles County
Homeownership Status				
Own	40.4	40.96	39.92	38.0
Rent	58.5	57.83	59.07	--
Other	1.1	1.20	1.01	--
Residence type				--
Single family home	47.0	48.4	45.6	
Multi-family home	35.1	36.3	33.9	
Duplex/triplex/Quad	8.2	5.4	10.8	
Townhome	6.2	6.1	6.4	
Mobile home	0.2	0.2	0.2	
Other	3.3	3.6	3.0	
Residence		12.02	10.52 (13.01)	
Mean (SD) length of tenure at current address	11.3 years (13.6)	(14.07)		--
% same house as last year	87.0			85.4
Household size				
Total	2.7	2.68 (1.67)	2.73 (1.58)	2.8

Procedures

Trained interviews conducted structured phone interviews with respondents. Respondents were selected at random from LADWP customer database. This included 500 SGRDP and 500 non-SGRDP customers. Surveys were conducted by Customer Research International, a phone survey and research company with whom the university researchers had previously worked. The mean duration of calls was 26 minutes.

Materials

Recruitment materials. Interviewers opened with an introductory recruitment statement. The recruitment script is provided in Appendix A.

Structured interview script/ survey. If participants were eligible and agreed to participate, interviewers read an IRB-approved information sheet prior to asking survey questions. Next, interviewers proceeded with survey questions, which included household characteristics, demographic characteristics, technology adoption, smart meters and related technology, energy efficiency. See Appendix B for survey items/structured interview script.

5. Summaries of the results of the performance of the smart grid systems and technologies derived from lab tests, field tests, or grid-connected applications.

The data gathered serve as a baseline against which we will compare changes in attitudes and behaviors relevant to smart grid systems and technologies. At this time, the data do not speak to this.

6. Summary of the major findings and conclusions including lessons learned and best practices.

Technology Use

The sample used communications and social media technologies fairly regularly. For instance, approximately 80% reported searching the web weekly, with 66% searching daily. Mobile phone text messaging was also common, reportedly used weekly by 80% and 70% used it daily. Social media use was less common, particularly twitter use, with only 14% of the sample accessing Twitter weekly, 31% reading or writing blogs, and 57% using Facebook weekly.

Table 3. Frequency of technology use reported by sample.

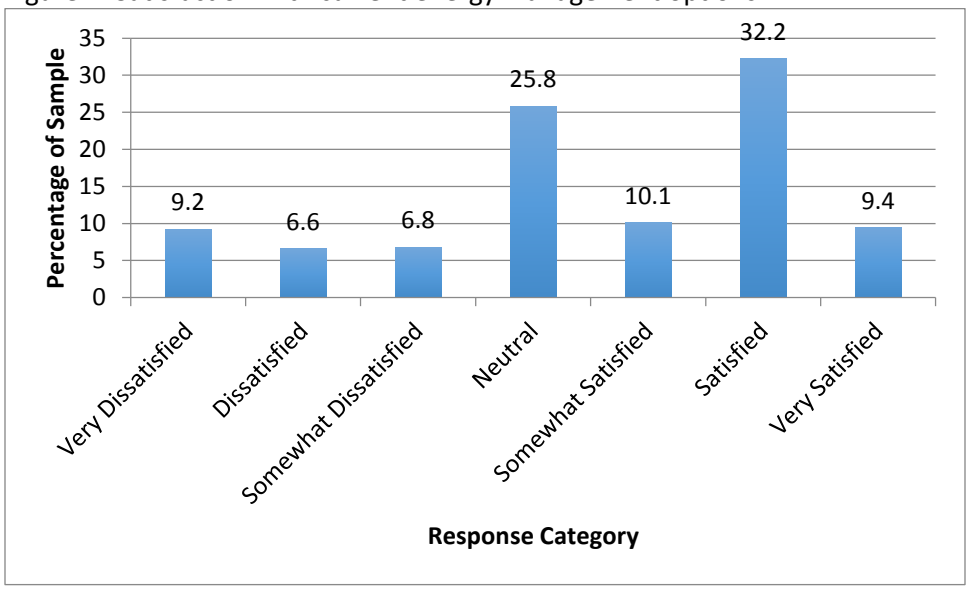
	Daily (%)	Weekly (%)
Search the web	66.2	80.3
Use email on computer	65.4	77.2
Use email on phone	61.0	67.3
Use email on tablet	30.1	41.7
Text	69.9	80.0
Use Facebook	41.4	57.4
Use Twitter	6.9	13.9
Access YouTube	21.6	53.4
Read or write blog	13.5	31.4
Other internet service	39.8	49.8

Energy Management Technologies

Respondents reported on a number of issues related to energy management technologies. None of the mean ratings differed based on SGRDP participant status.

First, approximately 51.6% stated they were at least somewhat satisfied with current energy management options offered by LADWP. The mean rating on a scale of 1 (very dissatisfied) to 6 (very satisfied) was 4.55 (SD = 1.76), suggesting that respondents in general felt fairly neutral, leaning slightly towards satisfied, about their energy management options. This may suggest a potential area of improvement. See Figure 1 below for additional details.

Figure 1. Satisfaction with current energy management options.



Preferences for energy management interface. Participants also rated their likelihood of monitoring their home energy consumption using a several different technologies: free website, free mobile phone app, free in-home display. Most distributions were bimodal, with a cluster of participants unlikely or very

unlikely to monitor their usage using the technology, and another cluster that was likely or very likely. Overall, the most frequently endorsed option was the free in-home display, with 58.3% of respondents indicating they were at least somewhat likely to use this. The mean rating on a scale of 1 (very unlikely) – 7 (very likely) was 4.45 (SD = 2.15). Next, 54.4% of respondents were at least somewhat likely to monitor their home energy use with a free website. The mean rating on a scale of 1 (very unlikely) – 7 (very likely) was 4.27 (SD = 2.18). Finally, approximately 52% of respondents stated they would be at least somewhat likely to monitor their home energy use using a mobile phone app. The mean rating on a scale of 1 (very unlikely) – 7 (very likely) was 4.13 (SD = 2.27). See Figures 2, 3, and 4 below for details.

Figure 2. Likelihood of Monitoring Home Energy Use with Free Website

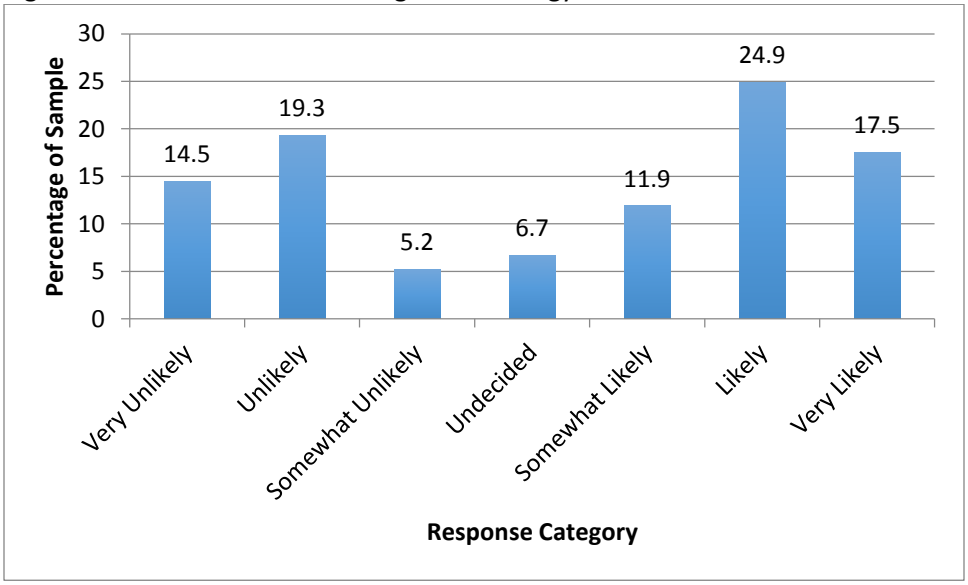


Figure 3. Likelihood of Monitoring Home Energy Use with Free Smart phone App.

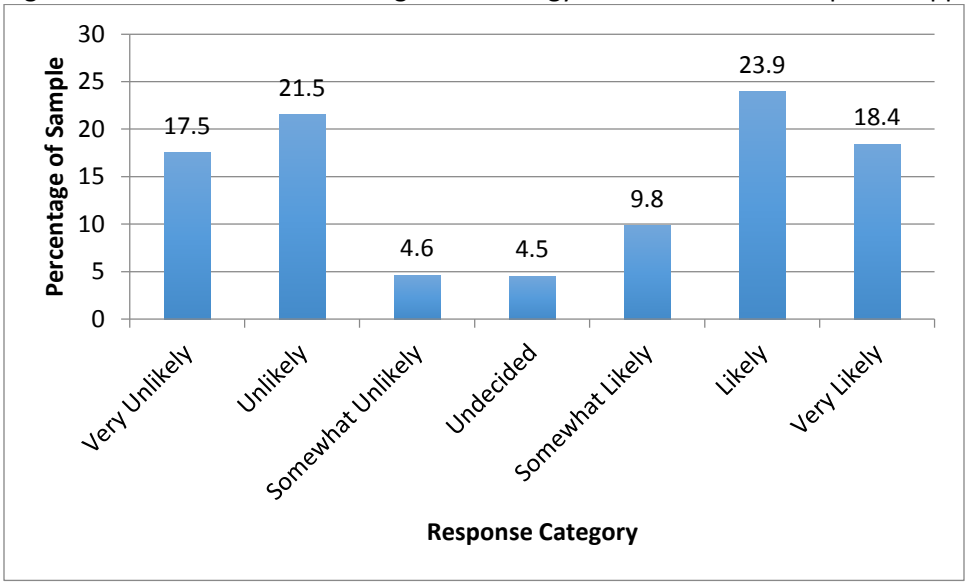
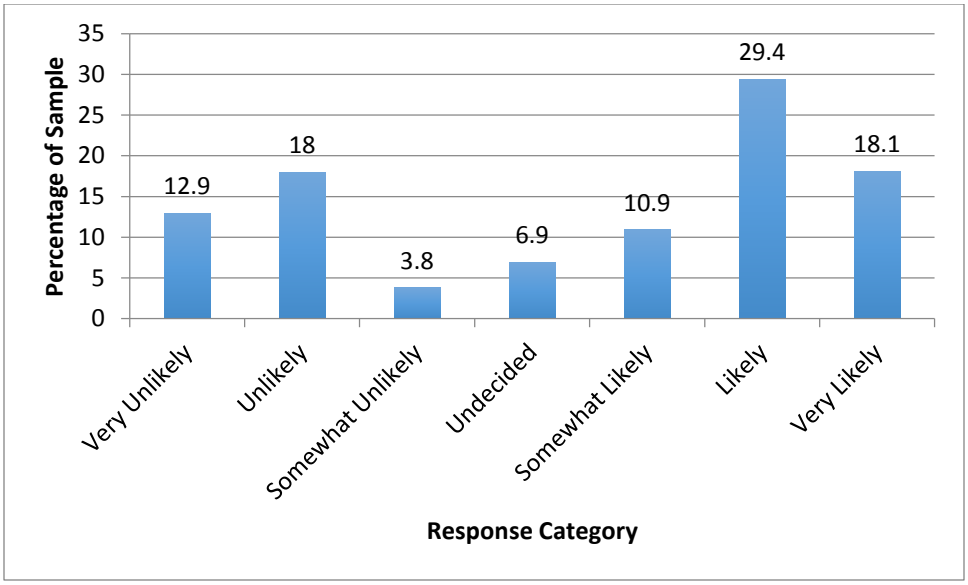


Figure 4. Likelihood of Monitoring Home Energy Use with Free In-Home Display.



Willingness to Participate in Programs. Participants were also queried about their willingness to participate in utility programs, including time-of-use pricing (TOU) and Save Power Events, both of which were described. Over half of participants (54.26) were at least somewhat likely to sign up for TOU pricing plan. The mean rating on a scale of 1 (very unlikely) – 7 (very likely) was 4.47 (SD = 2.0). More than two-thirds of the sample was at least somewhat likely to participate in a Save Power Event (69.53%). The mean rating on a scale of 1 (very unlikely) – 7 (very likely) was 5.23 (SD = 1.7). See Figures 5 and 6 below for details.

Figure 5. Likelihood of signing up for TOU pricing plan.

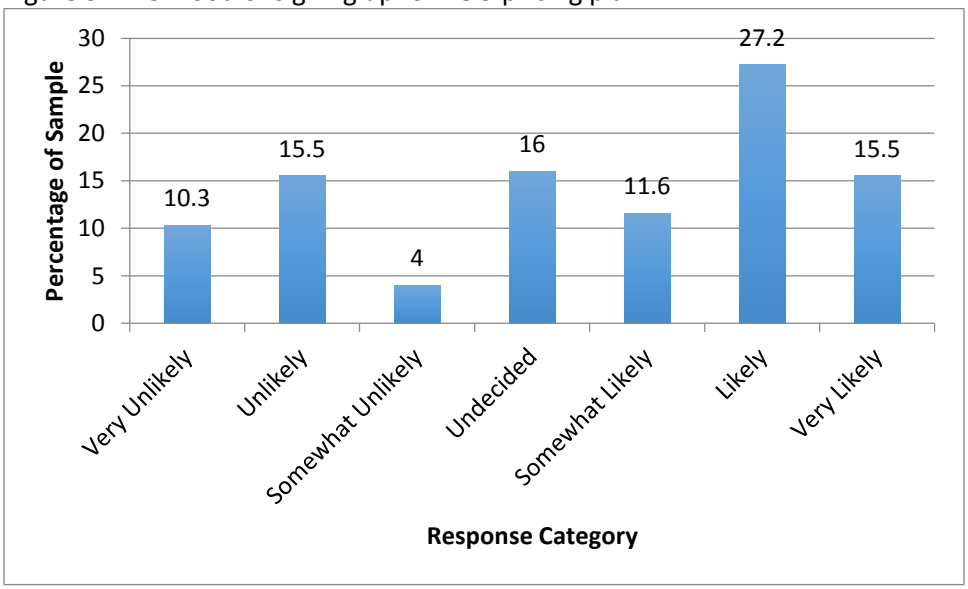
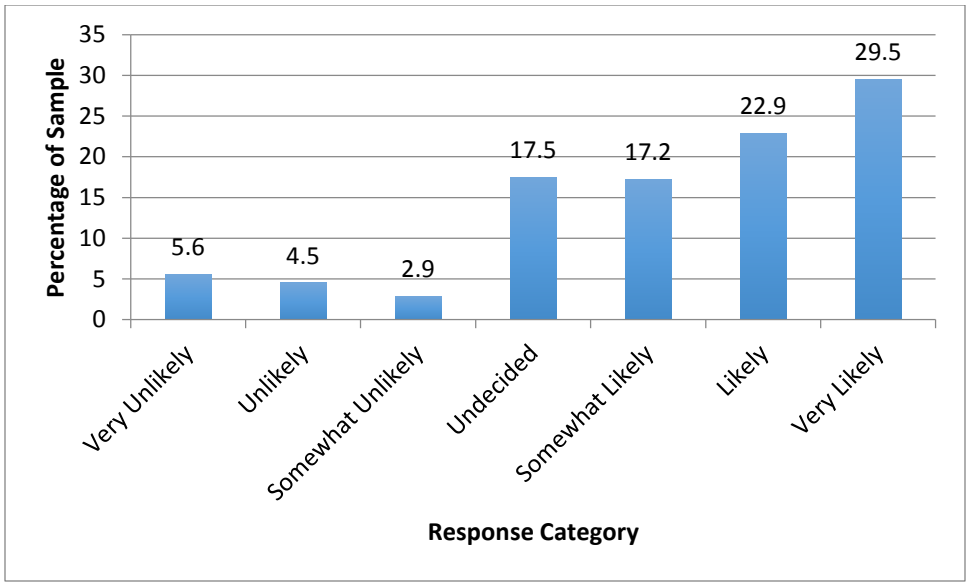


Figure 6. Likelihood of participating in a Save Power Event.



Beliefs Related to Smart Meters. Of SGRDP customers, only 27.2% correctly reported having a smart meter installed. Approximately 32.6% didn't know whether they had one, and 40.2% believed they did not have one. The same pattern of results was observed when restricting the sample only to those who directly paid their energy bills (e.g., rather than a spouse or roommate). This low rate of awareness suggests that meter notification methods could be improved. Multiple direct mail materials were sent to customers to notify them of installations. The findings here indicate that customers may have not seen the mail or did not attend to it. Alternatively, they may have forgotten about the meter between the time they received it and when they were surveyed, which ranged from 1 - 13 months.

Respondents indicated their level of knowledge about smart meters, their opinion, and to what extent they would accept a smart meter if LADWP planned to install one at their home. Over one-third of respondents had never heard of smart meters, and in general the sample had low levels of knowledge. This is in line with the above findings that many SGRDP participants were unaware they had smart meters installed at their homes. Interestingly, despite not knowing much about smart meters, respondents generally had neutral or favorable opinions towards them, and most indicated it would be acceptable if LADWP were to install meters at their homes. See Figures 7, 8 and 9 below for additional information.

Figure 7. Self-reported knowledge of Smart Meters.

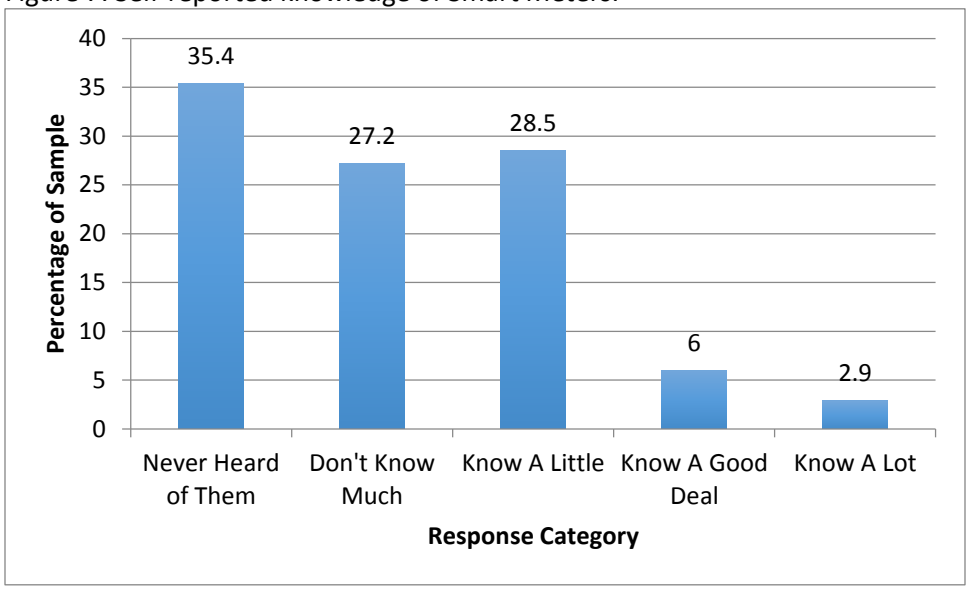


Figure 8. Opinion of smart meters.

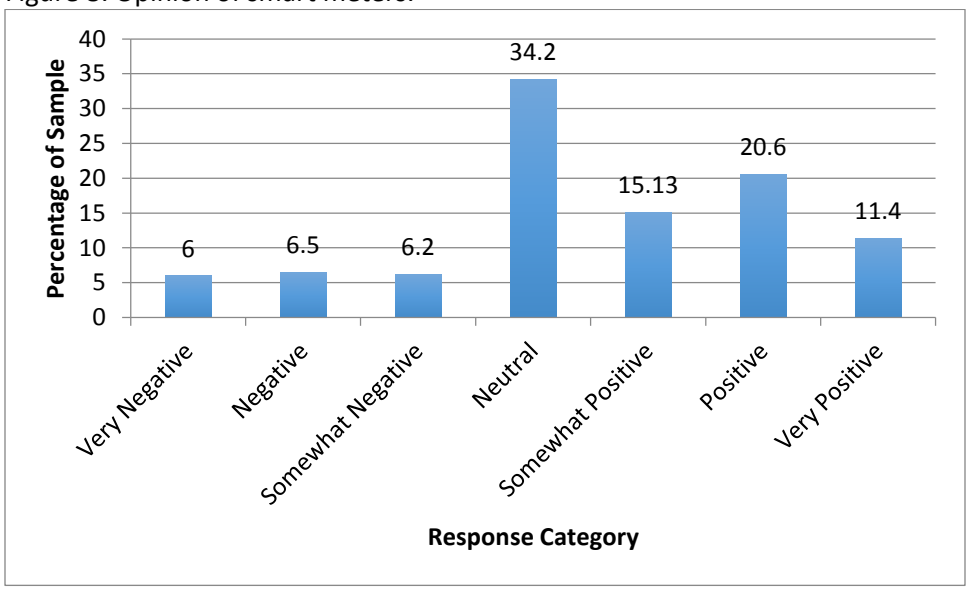
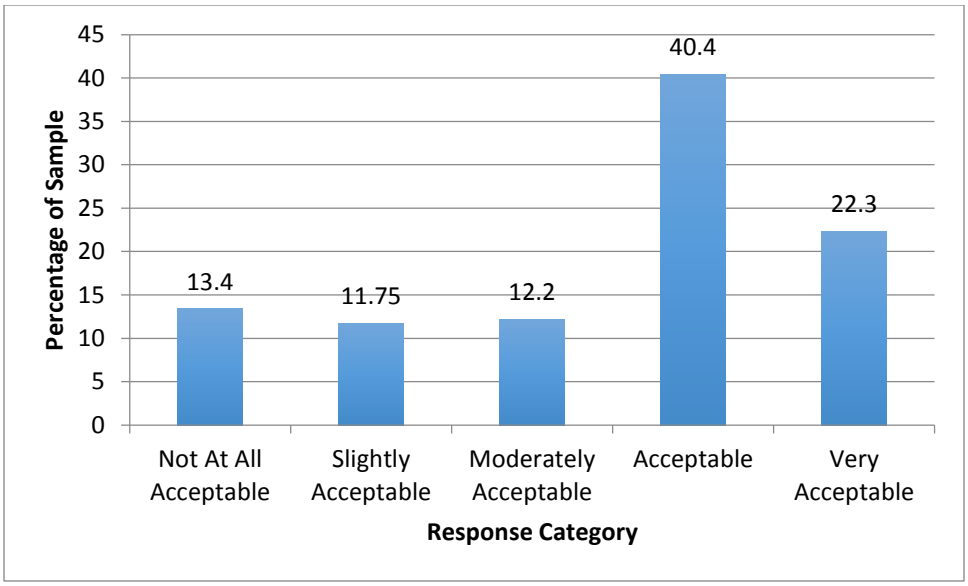


Figure 9. Acceptability of Replacing with Smart Meter.



Normative Influences

Normative influence refers to the influence of other people on one's own decisions and preferences. To better understand how normative influences could be leveraged to promote the adoption of smart grid technologies, we asked respondents questions related to normative influences on energy use. Respondents estimated the percentage of others in various categories that they believed were making effort to save energy. The groups included other Southern California residents, residents in the respondent's neighborhood, and residents on the respondent's particular street. Estimated percentages ranged from approximately 41% to 42%, demonstrating that respondents believed less than half of others around them were conserving energy. This is an area for improvement. Emphasizing descriptive norms that highlight the conservation efforts of others have been shown in other projects to promote conservation among target customers. This is also one of the key social science principles leveraged by OPower. Whereas the sampled believe that a moderate percentage of others were conserving, they believed they were performing at a superior level, and that they could achieve very high reductions. More than two thirds of the sample (69.71%) believed their household was conserving at least somewhat more than average. Clearly, for two-thirds of individuals in a group to perform better than the average of the group is impossible. The tendency for people to believe they are performing better than average is a common cognitive bias. They also reported that if their household made a special effort to conserve, they believed they could achieve a maximum of a 35.5% (SD=25.5%) reduction.

Table 4. Respondents' beliefs about energy conservation efforts of others.

Who is trying to conserve?	Mean % (SD)
Southern CA residents	40.9 (22.1)
Residents in your neighborhood	41.2 (25.4)
Residents on your street	42.3 (26.2)

Motivators for participating in energy efficiency

We sought to identify motivators for support smart grid systems that can be incorporated into messaging and outreach strategies. To this end, respondents indicated the extent to which they perceived various benefits of investing in smart grid to be per important to them personally. All motivators ranked relatively

high, with scores above 4.3 on a scale of 1 (not at all important) to 6 (extremely important). The highest-ranking motivators were: making our electric system more efficient (mean score = 5.06, SD = 0.73), reduce electric bill (mean = 4.98, SD = 0.86), and reducing greenhouse gas emissions and protecting the environment (mean = 4.98, SD = 0.96). Because these benefits resonated more with respondents than did others, these motivators can be incorporated into messaging strategies. In fact, these three top benefits of smart grid have already been incorporated into SGRDP program messaging.

Take-Away Points

- Many SGRDP respondents were not aware they had a smart meter installed at their home: only 27% correctly identified having a meter installed. This suggests that the multiple direct mail materials regarding meter installation were not opened, attended to, or perhaps forgotten about by participants.
- The sample also reported low levels of knowledge related to smart meters. Nonetheless, respondents reported neutral to favorable opinions related to smart meters.
- More than two-thirds of respondents were open to participating TOU pricing plans and Save Power Events.
- In terms of preferences for monitoring home energy usage, no major differences were observed, but in-home displays were slightly preferred.
- Participants tended to overestimate amount of energy they could save if they made an effort (36%). If participants set goals that cannot be achieved, they may become discouraged and stop trying. This finding suggests that energy awareness can be improved so participants are able to set realistic and achievable conservation goals.
- Overall, respondents believed that less than half of their neighbors were conserving energy. This suggests an opportunity to convey social norms about the energy conservation efforts of others that can motivate participants to conserve in their own homes.
- Based on perceived benefits of smart grid systems, the following benefits should be highlighted in SGRDP program messaging: environmental benefits, ability to control bill, efficiency of grid system

Limitations

We view the findings reported here in light of several limitations. Relative to the population of Los Angeles County, the sample under-represented Latinos and was over-educated. This may limit the generalizability of the findings. A potentially related limitation was the low response rate to the survey invitation calls, which may have resulted in sample bias whereby individuals who tended to have relatively higher levels of educational attainment and identified with non-Latino races agreed to participate. Response bias is a limitation common to all voluntary research studies that limits the generalizability of findings. An additional limitation, self-report data was the only data source for this baseline survey. At follow up, survey data will be combined with electricity consumption data and web portal usage data to understand how the demographic and psychosocial variables relate to energy consumed and other observed behaviors.

Strengths

Although the sample did not approximate racial and educational attainment of Los Angeles County population, it was roughly equivalent on all other available measures. Additionally, we used a structured interview format to obtain reliable and valid survey responses. Also, the data collected in this study provide the baseline against which we will compare SGRDP participant data. Though not reported here, we collected data to explore novel psychological phenomena related to the adoption of new technologies such as policy preferences and connectedness to nature.

7. Summary of future plans and next steps with respect to additional testing, demonstration, or deployment

The results of this survey will inform messaging and customer education and outreach efforts for Operations. In addition, these findings serve as a baseline against which follow-up survey data, to be collected at the end of the Operations period, will be compared. Including both SGRDP and non-SGRDP customers also enables us to explore differential rates of change among these subgroups. We hypothesize that attitudes towards energy management technologies and willingness to use these technologies will become more positive among SGRDP customers relative to non-SGRDP customers. Interacting with the program and engaging with energy data are hypothesized mediators of these changes.

8. Appendix: Supporting documentation and references

Appendix A: Telephone Script / Recruitment message

Hello, my name is _____. I'm calling on behalf of the University of Southern California and the Los Angeles Department of Water and Power, who have partnered to conduct a research study in your area to better understand attitudes and perceptions related to energy usage. Participation is voluntary. You must be aged 18 or older to participate.

Let me assure you that all of your responses will be kept confidential, and you may skip any question you do not wish to answer. You may also decide to stop participating at any time. If you decide to participate, I will ask you some questions over the phone, and record your answers. This will take approximately 15 minutes. Your responses may help us to better understand how people think about energy management in their homes.

The members of the research team, the funding agencies and the University of Southern California's Human Subjects Protection Program (HSPP) may access the data. The HSPP reviews and monitors research studies to protect the rights and welfare of research subjects.

When the results of the research are published or discussed in conferences, no identifiable information will be used.

If you have questions about the research, you are invited to contact the investigators. Dr. Nicole Sintov can be reached by phone at 310.448.9182 or by email at Sintov@usc.edu.

IRB CONTACT INFORMATION
University Park Institutional Review Board (UPIRB), 3720 South Flower Street #301, Los Angeles, CA 90089-0702, (213) 821-5272 or upirb@usc.edu
1=I would like to participate.

0=I DO NOT want to participate.

Appendix B: Survey / Structured Interview Script

S1. To be sure you're eligible to participate, can you please tell me whether or not you are over the age of 18?

1=YES. Thank you. We ask this question because we are only able to interview legal adults. In what year were you born? _____ (9999=REFUSED)

0=NO. I'm sorry, but we can only interview legal adults. Is there an adult over the age of 18 available right now?

1=YES. Can I speak with that person please?

1=YES. Great, I'll hold.

0=NO. Ok, thank you for your time. [end interview]

0=NO. I'm sorry, but I must end this interview. Thank you for your willingness to participate. If you have questions, you may contact Dr. Nicole Sintov can be reached by phone at 310.448.9182 or by email at Sintov@usc.edu.

My first few questions refer to your residence. If you have multiple residences, please respond only for your primary residence at which LADWP is your electricity provider. This information will remain confidential and will not be shared with anyone outside of the project team.

S1. What is the address of your primary place of residence?

Street address (e.g., 123 Main St. Apt 3): _____

City: _____

ZIP: _____

S2. How long have you lived at this address?

(99=REFUSED)

_____ years

S3. Do you own or rent this residence

1=Own

2=Rent

8=Other (please specify) _____

9=(REFUSED)

S4. Including you, how many people live in your household? _____ (99=REFUSED)

S4a. And how many of these are children under age 18?_____ (99=REFUSED)

S4b. And how many of these are adults?_____ (99=REFUSED)

S5. How would you describe your residence? Is it a . . . (READ)

1=Single family home (detached or free-standing residence)

2=Multi-family home (apartment, condo)

3=Duplex, triplex, or 4-plex

4=Townhouse

5=Mobile home

8=Other (please specify) _____

9=(REFUSED)

S6. Who in your household is responsible for paying your electric bill?

(SELECT ALL THAT APPLY) (READ LIST AS NECESSARY)

1=Yourself

2=Spouse or partner

3=Roommate

4=Parent or grandparent

5=Child or grandchild

6=Landlord or building management

7=Boss

88=Other (please specify) _____

9=(REFUSED)

S7. What is your annual household income? Is it . . . (READ)

1=Under $25,000

2=$25,000 - $50,000

3=$50,001-$75,000

4=$75,001-$100,000

5=More than $100,000

9=(PREFER NOT TO ANSWER)

SECTION 1: TECHNOLOGY

Next, I'm going to ask you about your use of various technologies.

101. For each of the following, please tell me if you do this activity Daily, 2-3 times a week, once a week 2-3 times a month, once a month, less than once a month, or never. First, how often do you . . .

1=Daily

2=2-3 times a week

3=Once a week

4=2-3 times a month

5=Once a month

6=Less than one a month

7=Never

9=(REFUSED)

a. Search for things online/ on the internet

b. Check email on a computer

c. Check email on your mobile phone

d. Check email on your tablet device (e.g., iPad)

e. Send or receive text messages on your mobile phone

f. Use Facebook

g. Use Twitter

h. Check out videos on YouTube

i. Read or write Blogs

j. Use other internet-based service (please specify)

102. How satisfied are you with the current home energy management options provided to you by LADWP? Would you say you are . . . (READ)

7=Very Satisfied

6=Satisfied

5=Somewhat Satisfied

4=Neutral

3=Somewhat Dissatisfied

2=Dissatisfied

1=Very Dissatisfied

9=(REFUSED)

103. For each of the following, please tell me if you are Very likely to do this activity, Likely, Somewhat likely, Undecided, Somewhat unlikely, Unlikely, or Very unlikely to do this activity. First, how likely are you to . . .

7=Very likely

6=Likely

5=Somewhat likely

4=Undecided

3=Somewhat unlikely

2=Unlikely

1=Very unlikely

9=(REFUSED)

a. Use a free website to manage your home energy use

b. Use a free smart phone app to manage your home energy use

c. Use a free in-home display to manage your home energy use

d. Switch to a time of use rate (higher rate during daytime hours, lower rate at night)

SECTION 2: SMART METERS

The next few questions are about “Smart Meters”. By Smart Meter, I am referring to smart electric meters which record how much electricity is being used at your home.

201. How would you rate your knowledge of "Smart Meters"? Would you say . . . (READ)

1=You have never heard about them

2=You don't know much about them

3=You know a little bit about them

4=You know a good deal about them

5=You know a lot about them

9=(REFUSED)

202. What is your general opinion of Smart Meters? Would you say it is . . . (READ)

1=Very negative

2=Negative

3=Somewhat negative

4=Neutral

5=Somewhat positive

6=Positive

7=Very positive

8=I don't know enough about them to give an opinion

9=(REFUSED)

203. Do you currently have a Smart Meter?

1=Yes

2=No

8=Don’t know

9=(REFUSED)

(if response to previous question was “No” or “Don’t Know”)

204. How acceptable would it be if LADWP planned to replace your current electric meter with a Smart Meter? Would it be . . . (READ)

5=Very Acceptable

4=Acceptable

3=Moderately Acceptable

2=Slightly Acceptable

1=Not At All Acceptable

9=(REFUSED)

SECTION 3: “SAVE POWER” PROGRAM/ENERGY CONSERVATION

At some point in the future, LADWP will be starting a voluntary "Save Power" program. Under this program, Save Power Events will occur, an estimated 5-10 days per year and will last a few hours each. The goal will be to reduce power usage during that time period. You can participate in one event or in all of them, whatever you chose. Prior to such events, LADWP will notify customers to inform them that a Save Power Event is going to occur. During Events, customers who choose to participate will do energy saving actions that are not too uncomfortable or inconvenient (e.g., turn down air conditioning a couple of degrees).

301. How likely are you to participate in a Save Power Event? Would you say you are . . . (READ)

7=Very likely

6=Likely

5=Somewhat likely

4=Undecided

3=Somewhat unlikely

2=Unlikely

1=Very unlikely

9=(REFUSED)

302. How much extra would you be willing to pay on your electric bill each month to have your electricity come from "green" power sources, such as solar and wind?

_____ Dollars ($) per month (999=REFUSED)

303. How acceptable are the following policy measures aimed at making households more energy efficient? For each, please tell me if it is Very acceptable, Acceptable, Moderately acceptable, Slightly acceptable, or Not at all acceptable. First, how acceptable is it to . . . .

5=Very Acceptable

4=Acceptable

3=Moderately Acceptable

2=Slightly Acceptable

1=Not At All Acceptable

9=(REFUSED)

a. Increase prices of appliances that are not energy efficient by 10%. Revenues are used to stimulate further development of energy-efficient appliances.

b. Increase prices of appliances that are not energy efficient by 10%. Revenues are used to reduce national debts.

c. Increase prices of appliances that have not been produced in an energy-efficient way by 10%. Revenues are used to develop techniques that reduce energy use for the production of appliances.

d. Increase prices of appliances that have not been produced in an energy-efficient way by 10%. Revenues are used to reduce national debts.

e. Increase prices of regular electricity by 10%. Revenues are used to generate more green electricity (e.g., by building wind farms).

f. Increase prices of regular electricity by 10%. Revenues are used to reduce national debts.

g. Subsidize energy-efficient appliances so as to make them 10% cheaper. Subsidies are funded from energy taxes charged on appliances that are not energy efficient.

h. Subsidize energy-efficient appliances so as to make them 10% cheaper. Subsidies are paid from general public funds.

i. Subsidize appliances that are produced in an energy-efficient way so as to make them 10% cheaper. Subsidies are funded from energy taxes charged on appliances that are not energy efficient.

j. Subsidize appliances that are produced in an energy-efficient way so as to make them 10% cheaper. Subsidies are paid from general public funds.

k. Decrease prices of green electricity by 10%. Subsidies are paid from an ecotax charged on regular energy.

l. Decrease prices of green electricity by 10%. Subsidies are paid from general public funds.

304. Please rate the extent to which you agree or disagree with each of the following statements. For each statement, please tell me if you Strongly agree, Agree, Somewhat agree, are Neutral, Somewhat disagree, Disagree, or Strongly disagree. First . . .

7=Strongly agree

6=Agree

5=Somewhat agree

4=Neutral

3=Somewhat disagree

2=Disagree

1=Strongly disagree

a. You often feel a strong connection to nature.

b. You think of nature as a family that you belong to.

c. You see yourself as a part of the greater circle of life.

d. You feel that all living things in this world are connected, and you are a part of that.

e. Like the tree in the forest, you feel you belong to nature.

"Smart grid" refers to technology being used to bring electricity delivery systems into the 21st century, using computer-based remote control and automation. Two-way communication technology and computer processing that have been used for decades in other industries makes these systems possible. They offer many benefits to utilities and consumers, including improved energy efficiency on the electricity grid and in utility customers' homes and offices.

305. Which of the following benefits of investing in a "smart grid" would be most important to you personally? For each, please tell me if this would be Extremely important, Very important, Somewhat important, Somewhat unimportant, Very unimportant, or Not at all important. First . . .

6=Extremely important

5=Very important

4=Somewhat important

3=Somewhat unimportant

2=Very unimportant

1=Not at all important

9=(REFUSED)

a. Making our electrical system more efficient

b. Reducing our dependence on fossil fuels

c. Improving our aging electric infrastructure

d. Greater choice in how much you pay for electricity

e. Greater control over your electric bill

f. Tell you how much electricity each of your appliances is using

g. Improving resilience against attack and natural disaster

h. Fostering economic growth and creating jobs

i. Better integration of renewable sources of electricity (e.g., solar)

j. Ability to support a growing number of plug-in electric vehicles

k. Reduce the risk of blackouts and brownouts

l. Reducing greenhouse gas emissions and protecting the environment

m. Better able to monitor your home energy use

n. Reduce your electric bill

306. Compared to the average Southern California resident, to what extent do you try to conserve electricity at home? Would you say you try to conserve electricity at home . . .
7=Much More Than Average

6=More Than Average

5=Somewhat More Than Average

4=About The Average

3=Somewhat Less Than Average

2=Less Than Average

1=Much Less Than Average

9=(REFUSED)

307. What percent of Southern California residents do you believe try to conserve electricity at home?

____ (0-100%, 999=REFUSED)

308. What percent of residents in your neighborhood do you believe try to conserve electricity at home?

____ (0-100%, 999=REFUSED)

309. What percent of residents living on your particular street do you believe try to conserve electricity at home?

____ (0-100%, 999=REFUSED)

310. If you and the other people you live with made a special effort to conserve energy, what is the maximum amount of energy reduction you think could be achieved? (0-100%)

____ (0-100%, 999=REFUSED)

311. Please indicate the extent to which you agree or disagree with the following statements. For each, please tell me if you Strongly agree, Agree, Neither agree nor disagree, Disagree, or Strongly disagree. First . . .

5=Strongly agree

4=Agree

3=Neither agree nor disagree

2=Disagree

1=Strongly disagree

9=(REFUSED)

a. You can count on your neighbors for help if you find yourself in any kind of trouble

b. Your neighbors have borrowed something from you or your family

DEMOGRAPHICS

This survey is almost done. Please tell us a bit about yourself.

D1. RECORD GENDER BY OBSERVATION

1=Male

2=Female

D2. What is the primary language you speak at home?

1=Armenian

2=Cantonese

3=English

4=Hindi

5=Japanese

6=Korean

7=Mandarin

8=Spanish

9=Russian

10=Tagalog

11=Vietnamese

88=Other (please specify) _____

99=(REFUSED)

D3. With which ethnic category do you most strongly identify?

1=African or African American

2=Asian or Asian American

3=Caucasian/white

4=Latino/a

5=Native American or Pacific Islander

6=Multiracial

88=Other (please specify) _____

99=(REFUSED)

D4. What is your marital status?

1=Never married

2=Currently married

3=Currently in a domestic partnership

4=No longer married

5=Separated

9=(PREFER NOT TO ANSWER)

D5. What is the highest level of schooling that you have completed?

1=Less than high school

2=High school / GED

3=Technical or trade school

4=Some college or Associate's degree

5=4-year college graduate

6=Completed graduate school or professional degree program

9=(REFUSED)

D6. What do you consider to be your political orientation? Would you say you are . . .
1=Very liberal

2=Liberal

3=Somewhat liberal

4=Moderate

5=Somewhat conservative

6=Conservative

7=Very conservative

9=(REFUSED)

D7. This survey is part of a longitudinal study of beliefs and opinions about energy management and related technologies. There is a follow-up survey planned in approximately 2 years. May we contact you in the future to request your participation in a follow-up survey? If you say yes, you may still decide not to participate in the future.

1=Yes

2=No

(IF YES) Great, thank you. What is the best contact number for you?

(If the respondent indicates the line you called, ask) Is there another number in case this one changes?

PRIMARY PHONE:_____

ALTERNATE PHONE:_____

Thank you for your participation. We appreciate your time. Have a great day.

Interviewer, please add the following information provided to you by LADWP to each respondent's record:

Customer Name

Customer Address

Customer phone number

Appendix G Summary of Findings from Pre-Operations SmartPower Partners Program

Summary of Findings from Pre-Operations SmartPower Partners Program

Los Angeles Department of Water and Power Smart Grid Regional Demonstration Program

Customer Behavior Project

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1. Change History

Author(s): Nicole Sintov

Reviewer/Approvers: Adam Chhan

2. Executive Summary

Significance. Approximately 40% of the energy consumed in the United States in 2012 was used by residential and commercial buildings (US EIA, 2013). To mitigate expanding energy needs and corresponding environmental and economic consequences of energy use, it is important to manage energy demand.

Project Goals. The goal of the present study was to develop and implement a behavioral intervention aimed to promote overall energy conservation and participation in several demand response events. An additional objective of the study was to evaluate the relative effectiveness of two different goal-setting techniques.

Method. A website-based behavioral intervention was delivered to a total of 49 Los Angeles Department of Water and Power residential customers located in the Northridge, CA area in Summer 2013. The website included a number of techniques that have received empirical support for reducing energy use, including goal-setting and historical and normative energy feedback. Participants were randomly assigned to 1 of 2 experimental groups. In the Simple Goal condition, participants set an energy reduction goal (e.g., reduce home energy use by 10%) for the subsequent two weeks. In the Enhanced Goal condition, participants not only set an energy reduction goal, but were also guided through a process whereby they selected from among a list of behaviors that they agreed to perform in order to achieve their goal. Several weeks later, all participants were contacted and asked to log in to the website to check whether they had achieved their goals.

Results. We examined energy use during participants' first goal periods, when engagement levels were likely to be highest. During initial goal periods, use declined by 0.80% across the sample. Basic users increased by 5.90%, whereas Enhanced users decreased by 7.48% on average. These results were not sustained across the 3-month intervention period: participants used 29% more electricity during the intervention relative to baseline. There were no group differences observed in this overall rate of change. In addition to general conservation, participants were also asked to take part in a total of three Demand Response (DR) events. Usage during DR events was 10-35% lower than usage during temperature-matched non-DR days. Examining DR results by group, usage among Enhanced users was significantly lower than that among Basic users during the first two events. There were no group differences for the 3rd DR event. We also observed that Enhanced users logged into the goal page an average of 7 times relative to 5 times among Basic users.

Conclusions. The fact that Enhanced users performed better than Basic users during DR events 1 and 2 suggests that the action planning step required of Enhanced users may have made energy saving more salient in general, and contributed to the observed group differences. Enhanced users also conserved energy during their first goal periods, whereas Basic users increased their usage. Although these results were not maintained across the entire 3-month intervention period, the other findings favored Enhanced users, suggesting that action planning can have a positive impact on energy use in both energy conservation and demand response. The larger but non-significant number of goal page views among Enhanced users suggests

that exposure or engagement may have mediated the group differences. Future research should explore this topic further. Several lessons learned were gained from the study and are detailed below.

3. An overview of the Demonstration

a. Smart grid capabilities and functions demonstrated

The present study demonstrated the following functions from the SOPO:

1. Demonstrate the impact of smart grid communication systems and processes on customer usage patterns.
2. Demonstrate effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns.
3. Demonstrate the introduction and trial of new energy-related information and interface technologies to energy use data and information
4. Demonstrate communication and media content on Smart Grid deployment, incorporating changes observed in awareness, attitudes, and energy use behaviors.
5. Demonstrate energy savings resulting from the use of smart grid enabled interfaces, pricing options and programs.

b. Smart grid impacts and benefits demonstrated

Approximately 40% of the energy consumed in the United States in 2012 was used by residential and commercial buildings (US EIA, 2013). To mitigate our growing energy needs and corresponding environmental, economic, and social consequences of energy use, it is important to manage energy demand. As new energy monitoring technologies become more prevalent (e.g., smart electric meters), information previously unavailable to building occupants is becoming readily accessible, offering new possibilities for effecting change in and parameterizing human behavior as part of energy management systems to achieve energy efficiency goals. Utilities, private companies, and researchers are developing dashboards, in-home displays, and mobile phone applications that visually display building electricity use with the goal of changing human behavior. However, most of these systems communicate one-way, from building to user. Instead of this model, a two-way, real-time communication system offers novel opportunities for engaging occupants and modeling their behavior. To enhance connectivity and participation, programs must shift from a one-way, utility-to-customer approach to a two-way, interactive relationship. Programs need to add value to customers' lives: tangible benefits, relatable energy information, and enjoyment.

The present study demonstrated how programs focused on changing customer behavior can lead to energy efficiency and load curtailment. Additionally, the present study unpacked the process of energy conservation goal setting by examining the effects of creating an "action plan" in conjunction with setting a goal relative to those associated with simply setting a goal. Using survey data, this project will also identify and describe different population segments based on attitudes toward smart meters, smart grid, and energy management technologies, among other variables. Such knowledge can be used to shape messaging strategies for future energy conservation programs.

c. List of objectives/Scope

The primary aim of this study is to evaluate the effectiveness of a web-based energy conservation intervention in reducing home energy use. A secondary aim is to examine the incremental effectiveness of action plan creation in conjunction with goal setting, relative to goal setting alone, in reducing home energy use.

d. Mapping to the SOPO & Deliverables

The following deliverables from the SOPO are presented in this report:

6. Identification of the effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns.
7. Identification of the key socio-demographic and community structure variables in the Smart Grid adoption process.
8. Identification of the key decision factors in the adoption of Smart Grid related technologies.
9. Integration of behavioral and social factors into the design and implementation of Smart Grid information architecture, data management, and cyber-security systems.
10. Deliver comprehensive data, analysis, and models relating socio-demographic compositions and customer use types to Smart Grid technology acceptance and use patterns.
11. Develop and test applications for a broad array of customer interfaces to energy information including an understanding of the impacts of emerging social media (such as Face book, Twitter, etc.)
12. Periodic reports documenting the results of the demonstration.

4. Summary of Background Literature

A total of 50 studies on residential energy reduction interventions were reviewed for their effectiveness in decreasing residential energy consumption. The intervention strategies employed by these studies can be divided into the 2 main categories of antecedents and consequences based on the principles of learning theory (Skinner, 1953). Antecedents are environmental stimuli presented prior to the performance of a behavior and serve as cues or facilitators of the target behavior prior to its performance. In contrast, consequences are administered following a behavior, and include both reinforcers, or stimuli that increase likelihood of a behavior being performed again, and punishers, or stimuli that decrease likelihood that a behavior will be performed again.

Antecedent Strategies: information, modeling, home audits, prompts, goal setting/commitment

Simple written or verbal information is quite common, and was included as an independent condition or combined with other intervention components in 34 of the 50 intervention programs reviewed. This strategy is not very well-supported in reducing energy use, however, and is less significantly effective when relative to other intervention strategies (e.g., Seligman & Darley, 1977; Winett et al., 1978). It may be best used as an adjunct to other strategies.

Modeling interventions can significantly reduce home energy use compared to pre-intervention levels (Staats et al., 2004; Winett et al., 1982), particularly when modeling stimuli are tailored to the target audience (Winett et al., 1985). Booster sessions or longer modeling intervention durations may be necessary to maintain positive effects of modeling. Home audit programs also show promise in reducing energy use over time (Blasnik et al., 2005; Hirst & Grady, 1982-1983; Roth et al., 2005; Winett et al., 1982-1983) and compared to control conditions (Hirst & Grady, 1982-1983; Winett et al., 1982-1983).

The evidence of written prompts in reducing home energy use is limited, although an automatic signaling device was significantly effective in reducing electricity use over time and compared to a control group (Becker & Seligman, 1978). In this study, the prompt was a flashing light that could only be stopped if the participant turned off the air conditioner, so the target behavior (i.e., turning off the air conditioner) became a negative reinforcer. Future work should investigate prompts that effectively make the target behavior a negative reinforcer.

Goal setting and commitment have only been applied in conjunction with other intervention strategies, most often feedback and information (e.g., Katzev & Johnson, 1984; Winett et al., 1979; Winett et al., 1982). This combination strategy may operate through inducing cognitive dissonance when feedback or information highlights that stated goals have not been met. The evidence supports the effectiveness of these combined strategies in reducing home energy use, particularly when goals and commitments are made publicly (Pallak & Cummings, 1976), pledges made are relatively difficult, and feedback on goal attainment is provided (Becker, 1978), though effects have generally not persisted through follow-up periods (Katzev & Johnson, 1984; Van Houwelingen & Van Raaij, 1989; Winett et al., 1979; Winett et al., 1982). Research in other

areas suggests that reminding individuals of prior commitments increases their likelihood of following through (Lipsitz et al., 1989). Future work in the residential energy use field should investigate the effectiveness of reminders as a maintenance strategy.

Consequence Strategies: feedback, rewards, time-of-use pricing

Descriptive feedback, or providing users with information on their own recent or historical energy use, is a very well supported strategy for reducing home energy use below baseline levels (Bittle et al., 1979; Midden et al., 1983; Van Houwelingen & Van Raaij, 1989), producing load shifting (Lutzenhiser et al., 2007; Martinez & Williamson, 2005), and energy savings relative to control conditions (Arvola et al., 2004; Bittle et al., 1979; Kantola et al., 1984; McClelland & Cook, 1979-1980; Petersen et al., 2007). Feedback frequency is positively related to its effectiveness (Petersen et al., 2007; McClelland & Cook, 1979-1980; Van Houwelingen & Van Raaij, 1989). Normative feedback, which involves providing users with information about energy use among neighbors, friends, or other meaningful social groups, has received mixed support, with some studies finding no differences between treatment groups who receive normative feedback compared to descriptive feedback (Abrahamse et al., 2007; Brandon & Lewis, 1999), and others finding enhanced savings among normative compared to descriptive feedback treatment groups (Midden et al., 1983; Pallak et al., unpublished). These mixed findings may be attributable to the boomerang effect described by Schultz et al. (2007) and identified in several other intervention studies (e.g., Brandon & Lewis, 1999; Van Houwelingen & Van Raaij, 1989) as an increase in energy use among initial low users of energy following the provision of normative feedback. To prevent this unwanted effect, normative feedback should be administered concurrently with injunctive feedback, which communicates overall approval or disapproval. Toward this end, smiley faces on energy bills have been effectively used (e.g., Schultz et al., 2007).

The bulk of the literature on rewards supports the short-term effectiveness of this strategy in promoting energy savings (e.g., Hayes & Cone, 1977; McClelland & Cook, 1980b; Winett et al., 1978). However, when rewards are withdrawn, effects achieved during the intervention typically do not persist. These findings suggest that external stimuli should not be relied on to maintain long-term behavior change. Interventions should facilitate a transition to intrinsic motivation whereby behaviors initially contingent on external stimuli become maintained by intrinsic factors within an individual (Deci & Ryan, 1985). To enable this, additional intervention components are likely needed, and intervention length should be extended, as short-term studies typically do not provide for sufficient time for natural consequences to gain control of maintaining the behavior (e.g., social approval; Geller, 2002).

Overall, the evidence supports TOU pricing in producing modest effects for load shifting, particularly when applied in combination with feedback (Arvola et al., 1984; Lutzenhiser et al., 2007; Martinez & Williamson, 2005; Pedesen, 2009; Sexton et al., 1987). TOU pricing is not currently supported for reducing overall use. Different rate structures should be tested to identify the optimum pricing structure.

Goals of present study

One gap in the literature is in understanding of mechanisms of behavior change: although the evidence supports the effectiveness of various strategies, it is not clear how or why they are successful. In the current study, baseline and follow-up assessment of psychosocial predictors of behavior change will provide for an examination of mechanisms of change. Ultimately, understanding how these tools drive behavior change is going to enable the development of more streamlined and targeted interventions. Next, the present study unpacked the process of goal setting by examining the effects of creating an "action plan" in conjunction with setting a goal relative to those associated with simply setting a goal. Using survey data, this project will also identify and describe different population segments based on attitudes toward smart meters, smart grid, and energy management technologies, among other variables. Such knowledge can be used to shape messaging strategies for future energy conservation programs.

Specific aims

1. The primary aim of this study is to evaluate the effectiveness of a web-based energy conservation intervention in reducing home energy use.
2. A secondary aim is to examine the incremental effectiveness of action plan creation in conjunction with goal setting, relative to goal setting alone, in reducing home energy use.

Hypotheses

1. Related to the primary aim of the study, we hypothesize that a significant decrease in home energy use will be observed during the intervention relative to the baseline period after controlling for within-subjects factors known to influence energy consumption such as outdoor temperature.
2. Related to the secondary aim, we hypothesize that individuals who create action plans in conjunction with energy reduction goals will consume less electricity than those who simply set goals.

5. Descriptions of the methodologies utilized

Procedures

The study used a prospective experimental design. Participants received a web-based energy efficiency and DR intervention from April-July 2013. They also completed baseline and follow-up surveys.

The intervention portion of the study was delivered via a custom-built web portal that was seamlessly merged with customers' LADWP web accounts. This web portal provided access to a suite of energy management tools (detailed below). During the study, participants could access the portal 24 hours per day, 7 days per week by logging into their existing LADWP accounts. They could choose to spend as little or as much time accessing the portal as they wished. They received reminder emails every two weeks reminding them to check their accounts.

The web portal launched in April 15, 2013 and closed on July 31, 2013. During this time, participants were granted access to new features/modules via their LADWP web portals. The purpose of this experiment was to identify the set of intervention tools associated with the highest levels of customer satisfaction and greatest reductions in overall electricity use. Participants were randomly assigned to different experimental groups, and were blind to their group assignment. When participants logged into their web portals, they were able to access modules corresponding to the group to which they were assigned.

Recruitment

Preselected households were mailed letters from LADWP notifying them of the opportunity to participate. Potential participants could respond to the inquiry via mailing back a postage-paid postcard with their contact information, by calling a study hotline, or by visiting the study website. Eligibility criteria was assessed either by phone or, if participants visited the website directly, via an online form. To be eligible, participants had to meet the following criteria:

- Be a current LADWP customer with an address on the pre-selected list
- Aged 18 or older
- Resided at the eligible residence for at least 6 months
- Report no plans to move before December 2012
- Establish an online "My Account" for their LADWP electric account if they did not already have one
- Report accessing the internet at least once per week
- Agree to participate in at least one Save Power Event during the program

Participants

A total of 3931 households received recruitment letters in March 2012. Of these, 431 customers responded to the solicitation, including 144 who met eligibility criteria. LADWP provided a total of 98 smart electric meters for this project. Accordingly, 98 customers from among the 144 eligible were randomly selected to receive a meter. Meters were installed in July and August 2012. Following installation, 2 meters failed, ceasing to transmit data for the duration of the project. These households were not included in the study. To enable communication of the meter with the web portal, participants were asked to provide their

LADWP.com usernames and email addresses. A total of 68 participants did so. Among these, 2 meters ultimately failed and ceased to transmit data, 1 participant moved, and an additional participant withdrew from the study in June 2013; these participants were not included in the study. After the web portal launched, the study team called and emailed remaining participants to notify them of the availability of the portal and the official start of the study. A total of 49 participants ultimately logged in and registered to use the portal. Delays between recruitment (April 2012) and the launch of the portal (April 2013) may have contributed to the relatively high attrition rate.

Of the 49 participants, 51% were male and 43% were female. Respondents ranged in age from 28 to 100 years, with 75% of the sample being 59 years of age or younger. Sixty-nine percent of participants were either married or in a domestic partnership, while 20% were divorced, widowed, separated or not married. Forty-five percent of participants considered themselves to be moderately politically oriented, while 31% indicated they were liberal and 18% indicated they were conservative. Looking closer at the household characteristics, 90% of participants indicated they lived in a single family home (detached or free standing residence). The majority of households included between 1 and 3 adults (76%), and had either no children under 18 (33%) or between 1 and 4 children under 18 (45%). The annual household income ranges varied; 18% of the sample earned $50,000 or below per year, 33% earned between $50,000 and $100,000 per year and 31% earned more than $100,000 per year. Please note that overall the percentages may not sum to 100% because answers were not provided to all survey questions.

Web portal functionality

All participants had access to the following modules within the web portal:

- Personal energy feedback. In this module, a line graph showed the household's daily electricity use for the preceding two weeks. Customers could select different time frames and were able to view up to four weeks of previous electricity consumption data at daily and 15-minute interval levels. Participants could choose to display consumption in terms of kWh, dollars (estimated), or pounds of carbon dioxide emitted.
- Normative feedback. In addition to the line depicting the customers' own usage, an additional line showed the average consumption of other SmartPower Partner households. When participants are performing better than the norm, this type of injunctive normative feedback has been associated with reductions in usage.
- Carbon footprint audit. A link to a carbon footprint calculator quiz (http://coolcalifornia.org/calculator) was provided where participants could enter data about their households and lifestyle choices that contribute to carbon emissions. A report was generated at the end of each quiz to raise awareness about impacts of energy use and help households identify behaviors that could be changed to have an impact on reducing their contributions.
- Badges. The badge earning function was akin to 4Square, a smartphone application whereby users earn virtual badges and statuses (e.g., "mayor") for frequenting business establishments. Likewise, this function in the energy management app had rules whereby customers earned different types of virtual badges for: participating in DR events, shedding load during a DR event, reducing overall consumption in a given time period, and participating in surveys. Badges could be downloaded to enhance the pride.
- Save Power Events. When Save Power Events were not under way, this page simply explained Save Power Events and, after events had been executed, displayed the date and time of the previous

events along with a graph depicting participants' usage during each. For each Save Power Event, participants received email notifications the day preceding each event and approximately an hour before the start of each event. They also received an email after each event notifying them that the event had ended and inviting them to participate in an online survey. Each survey was available for one week following the corresponding Save Power Event.

In addition to the above modules, participants were randomly assigned to one of two experimental goal-setting groups, each of which had its own unique functionality.

- Basic Goal Setting group. Participants in this group were asked to commit to an energy conservation goal of 10% (The 10% goal was set by experimenters based on survey data indicating that most participating households believed they could reduce their consumption by 10%). Goal periods were 2 weeks long, and at the end of each period, participants received an email message encouraging them to log in and see if their 10% reduction goal had been met. The goals module also included a screen with energy saving tips, which were divided into three categories based on impact: platinum, gold, and silver. Platinum behaviors had the biggest impact on household energy use, gold behaviors had less of an impact, and silver behaviors had the lowest impact.
- Enhanced Goal Setting group: This module included everything in the Basic Goal Module, but also required customers to create behavioral action plans when they set their 10% reduction goals. After agreeing to the 10% goal, customers viewed the same list of tips that was shown to the Basic Goal group, but instead of merely viewing the list, participants could check a box next to each behavior to indicate the actions they were willing to take during that goal period in order to achieve their goals. This is akin to a diet plan that allows dieters to mix and match daily or weekly menu choices given a particular caloric goal. Additionally, when Enhanced users logged back in to check on the status of their goals, they were taken through the list of actions they had previously indicated they would perform and asked if they followed through. They were also taken through the list of actions they did not agree to perform and asked if they ended up engaging in any of those behaviors. Customers then were asked to re-commit to the 10% goal and select behaviors they could commit to performing in order to get there. This functionality allows us to distinguish whether the mere setting of a goal motivates sustained behavior change or whether frequent self-monitoring bolsters motivation significantly more. Participants were not informed when they set goals or selected behaviors that they would be asked which they followed through with.

Data collection

Whole-house electricity use data was automatically collected by the "smart" electric meters in 15-minute intervals from March 15, 2013 through August 15, 2013 for the 96 households who volunteered to participate in the study. The data for this report are from the 49 participants who provided LADWP.com usernames and registered to use the portal. A total of 31 individuals who received meters did not provide LADWP.com usernames, and an additional 16 who provided usernames never registered to use the portal; these 47 households did not participate in the intervention and thus their data were excluded from the present analyses. The intervention period was April 15, 2013-July 31, 2013.

Historical electricity data was also gathered for all study residences. In accordance with LADWP billing cycles, bimonthly electricity consumption data for the two years preceding the intervention start date were provided by LADWP.

A baseline survey was administered following consent and study enrollment to assess demographics, technology access, and attitudes and opinions related to smart meters and related energy management technology. During the intervention phase, brief surveys were administered following each of the 3 Save Power Events to assess participation levels, reasons for participating or not, and specific behaviors undertaken during events. A follow-up survey was administered after the intervention period ended to assess overall satisfaction with the program and changes in opinions related to smart meters and energy management technology.

6. Summaries of the results of the performance of the smart grid systems and technologies derived from lab tests, field tests, or grid-connected applications.

Energy Use

Energy use during the intervention period was compared to use during baseline. Baseline was calculated using data from temperature-matched 2012 time periods.

As reported in Table 1 below, relative to baseline, energy use across the sample was 29% higher during the 3-month intervention time period. This is not surprising given typical southern California temperature fluctuations from spring to summer, along with the limited granularity of baseline data (bimonthly data). Examining results by group, during the intervention period, mean daily consumption among Enhanced users was higher (28.56 kWh/day) than among Basic users (25.90 kWh), but this difference was not significant based on a one-way ANOVA ($F(1, 36) = 0.79$, $p<.07$). See Figure 1 below for a visual representation of the results.

Table 1. Mean Daily Energy Use And Changes In Use During Various Study Time Periods (kWh).

Time period	All	Basic	Enhanced
Entire Intervention			
Temperature-matched Baseline	21.95	20.27	23.62
Intervention (entire intervention period)	27.23	25.90	28.56
% Change (Baseline vs. intervention)	29.04	29.14	28.95
First Goal Period			
Temperature-matched Baseline	21.07	20.22	22.50
First Goal Period	20.89	20.80	20.97
% Change (Baseline vs. First Goal Period)	-0.80	5.90	-7.48
Post-Intervention			
Temperature-matched Baseline	39.65	39.75	39.54
Post-Intervention	27.09	25.11	28.98
% Change (Baseline vs. Post-intervention)	-27.96	-31.56	-24.37

Figure 1. Energy Use During Intervention Period (4/15/13-7/15/13).

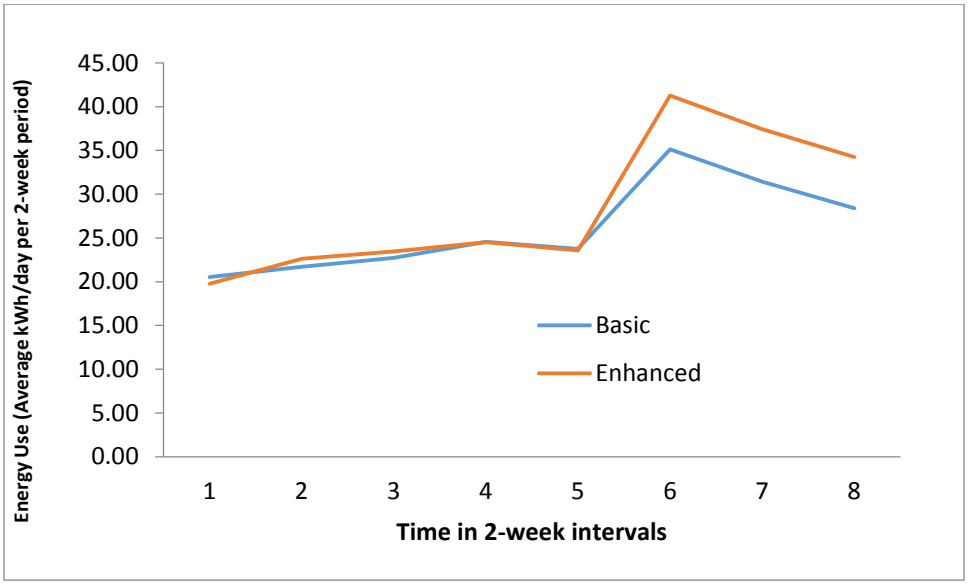


Figure note: n_{basic} = 18; $n_{enhanced}$ = 18

Changes in Use During Intervention Period

We also examined changes in usage from baseline to follow-up, a more meaningful test that adjusts for differences in the group baselines. As can be seen in Table 1, Enhanced users increased by 28.95%, whereas Basic users increased by 29.14%. Based on ANOVA analyses, the difference in these changes between the two groups was not significant, however ($F(1, 34) = 0$, $p < .99$). Nonetheless, these findings are in the desired direction, with Enhanced users performing slightly better than Basic users.

First Goal Period

We reasoned that the largest changes in behavior may occur during the first goal period while participants were more likely to be engaged, so we also examined energy use during each participant's first goal period. Note that these periods differed across participants, and baseline use was recalculated per user to match initial goal period temperatures as closely as possible. During their first goals periods, Basic users consumed a mean of 20.8 kWh/day, whereas Enhanced users consumed a mean of 21.0 kWh/day. Daily usage did not differ significantly between the 2 groups based on ANOVA results ($F(1, 35) = 0.004$, $p < .96$). See Table 1 above and Figures 2 and 3 below for details.

Figure 2. Mean Daily Energy Use During First Goal Period Among Full Sample (n = 37).

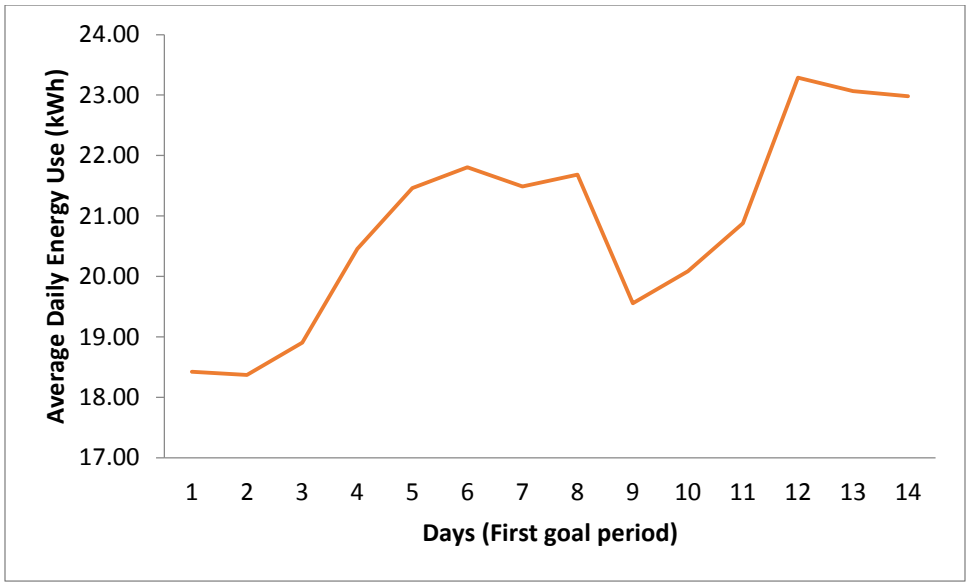


Figure 3. Mean Daily Energy Use During First Goal Period By Group.

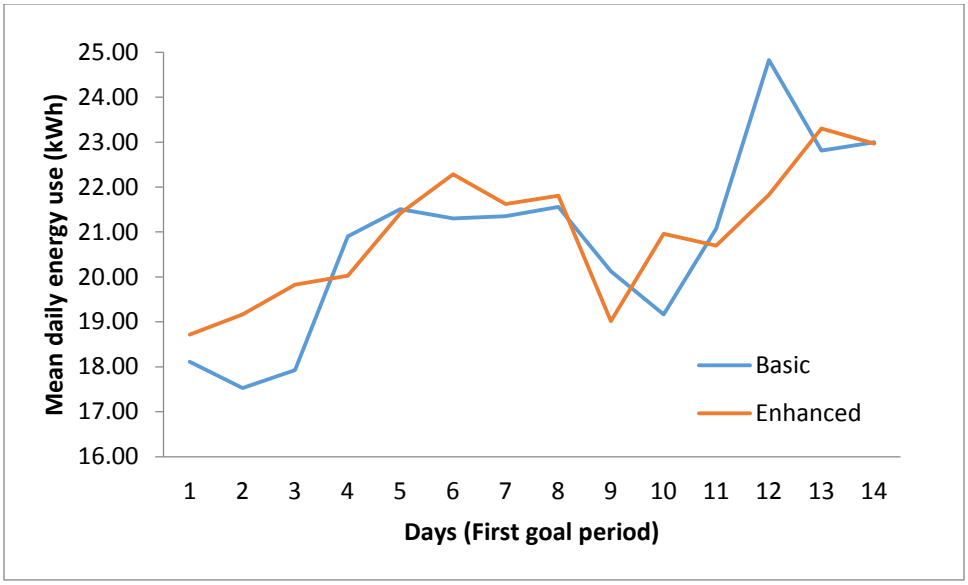


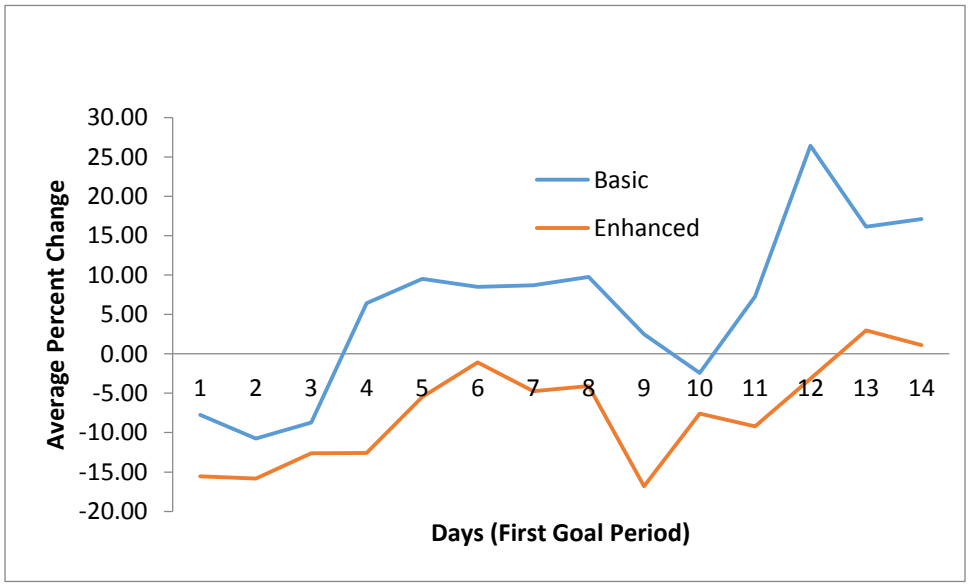
Figure note: n_{basic} = 18; $n_{enhanced}$ = 19.

Changes in Use During First Goal Period

In terms of change in energy use relative to baseline, overall, use declined by 0.80% during users' first goal periods. The average change in energy use among Basic users was an increase of 5.90%, whereas Enhanced users decreased by 7.48% on average. These changes did not differ significantly between groups based on a

one-way ANOVA (F (1, 34) = 0.09, p<.77). See Table 1 above and Figure 4 below for details. Though the findings were not statistically significant, Enhanced users performed better than did Basic users, which is in line with the smaller increase in use among Enhanced versus Basic users across the entire intervention period.

Figure 4. Change In Energy Use (Baseline vs. First Goal Period) By Group.



Post-Intervention

To explore the possibility of delayed effects, we examined energy use during the post-intervention period of July 16, 2013-August 1, 2013. New baseline daily averages were computed to match usage during time periods with similar temperatures to the post-intervention period. Overall, use among the sample was 27.96% lower during post-intervention relative to baseline, as can be seen in Figures 5 and 6 below. This decline *was* significant based on results of a t-test (t (35) = -6.79, p<.00). Nor did daily mean post-intervention usage differ between Basic and Enhanced users (F (1, 35) = 0.81, p<.38). Examining changes within each study group, mean daily energy consumption among the Basic group decreased by 31.96%, and among the Enhanced group by 24.37%. ANOVA results did not find significant differences in the change between the 2 groups (F (1, 34) = 1.13, p<.30)

Figure 5. Baseline And Post-Intervention Daily Average Use Among Basic Users

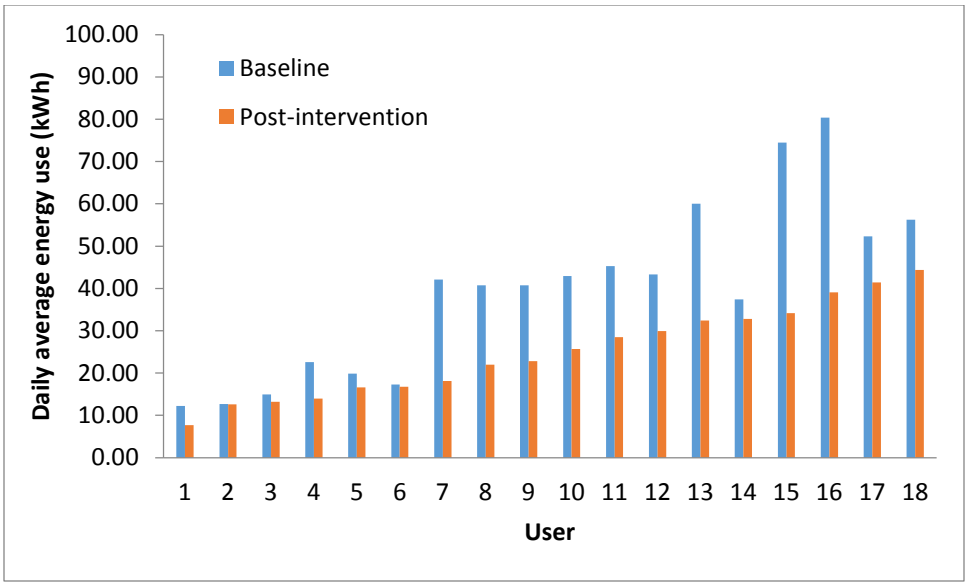


Figure note: n = 18

Figure 6. Baseline And Post-Intervention Daily Average Use Among Enhanced Users

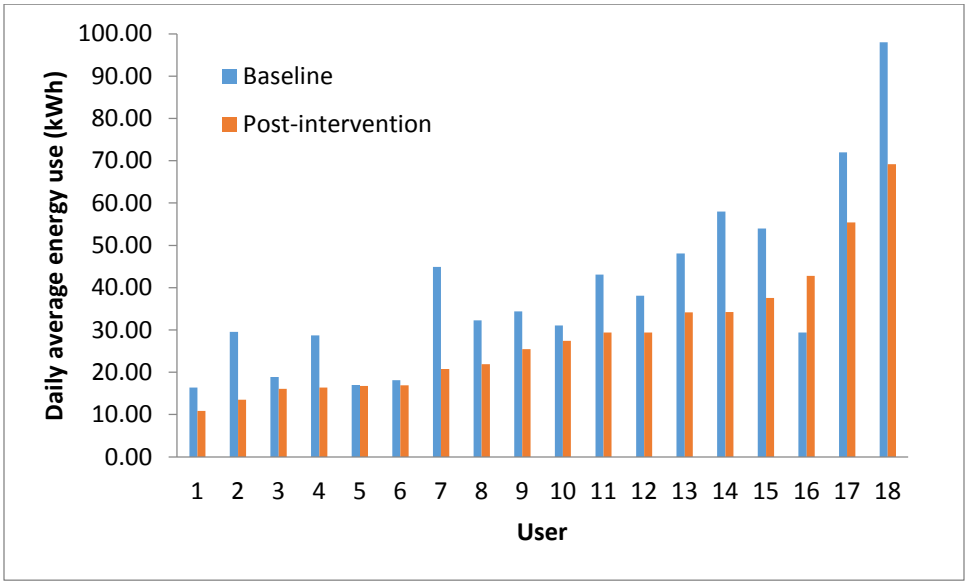


Figure note: n = 18.

Demand Response Events

Participants also took part in 3 Demand Response (DR) events. Figures 7, 8, and 9 depict usage by group during each event, respectively. We examined energy usage data from non-DR days that shared similar temperature profiles to the DR days. We observed that for DR events 1 and 2, mean consumption during the

same time period on non-DR days was 10-35% higher than on DR days, suggesting that the program had a positive impact on peak load curtailment.

For each DR event, we also examined group differences in the amount of energy consumed during the event time period. There was an effect for group during Events #1 ($t_{(12)} = 2.96$, $p<.02$) and #2 ($t_{(12)} = 3.42$, $p<.01$) whereby Enhanced users consumed significantly less energy than Basic users. No significant group effect was observed for Event #3 ($t_{(12)} = -0.03$, $p<.98$). Results are summarized below in Table 2.

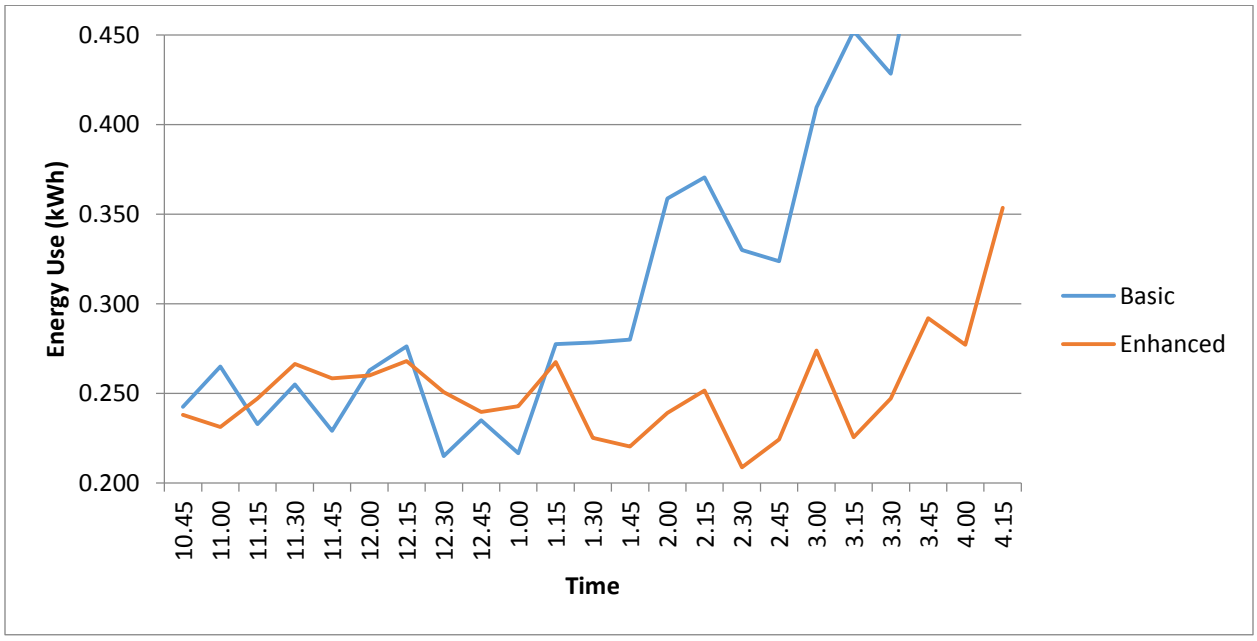
Table 2. Mean Energy Use During Demand Response Events and Expected Use.

	Basic Use (kWh)	Enhanced Use (kWh)	Basic Expected Use (kwh) [a]	Enhanced Expected Use (kWh) [b]
DR Event 1	3.83	3.17	5.93	4.19
DR Event 2	3.69	3.05	4.08	3.63
DR Event 3	8.59	9.24	NA	NA

[a] Event 1 expected use based on data from 6/2/13.

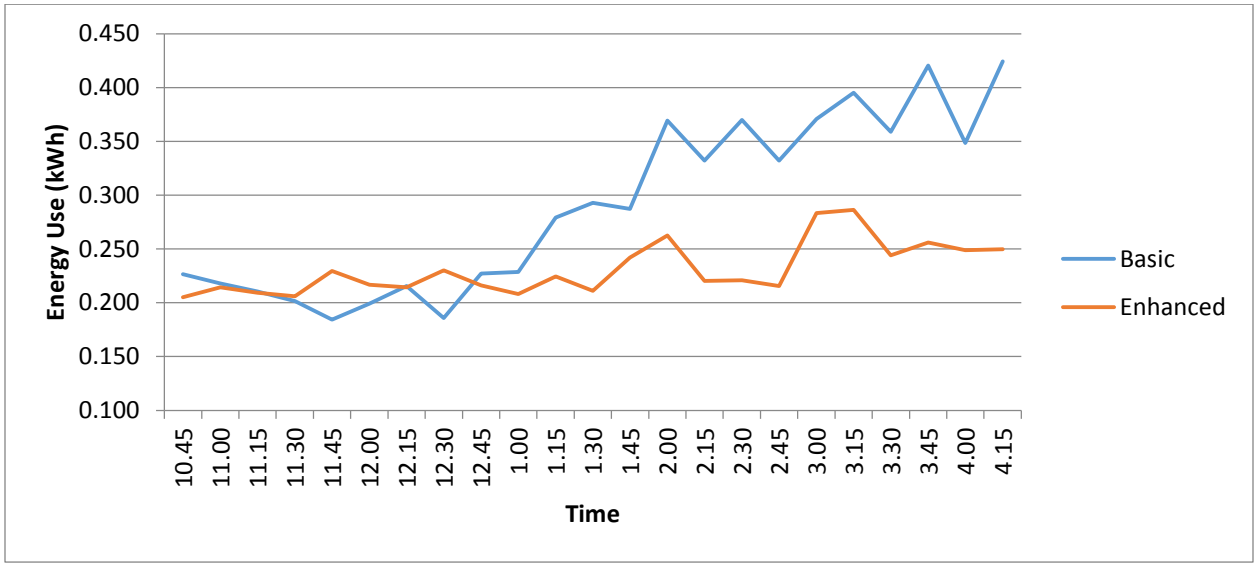
[b] Event 2 expected use based on data from 6/23/13.

Figure 7. Energy Use By Group During DR Event #1.



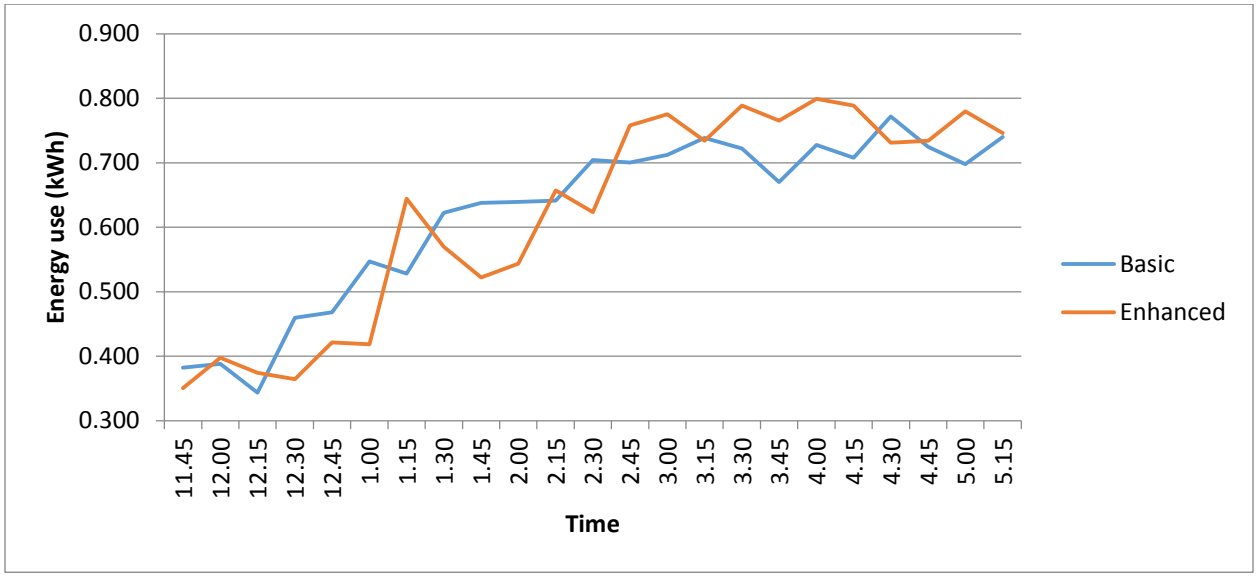
Note: DR Event duration was 12-3pm on 5/19/13.

Figure 8. Energy Use By Group During DR Event #2.



Note: DR Event duration was 12-3 pm on 6/9/13.

Figure 9. Energy Use By Group During DR Event #3.



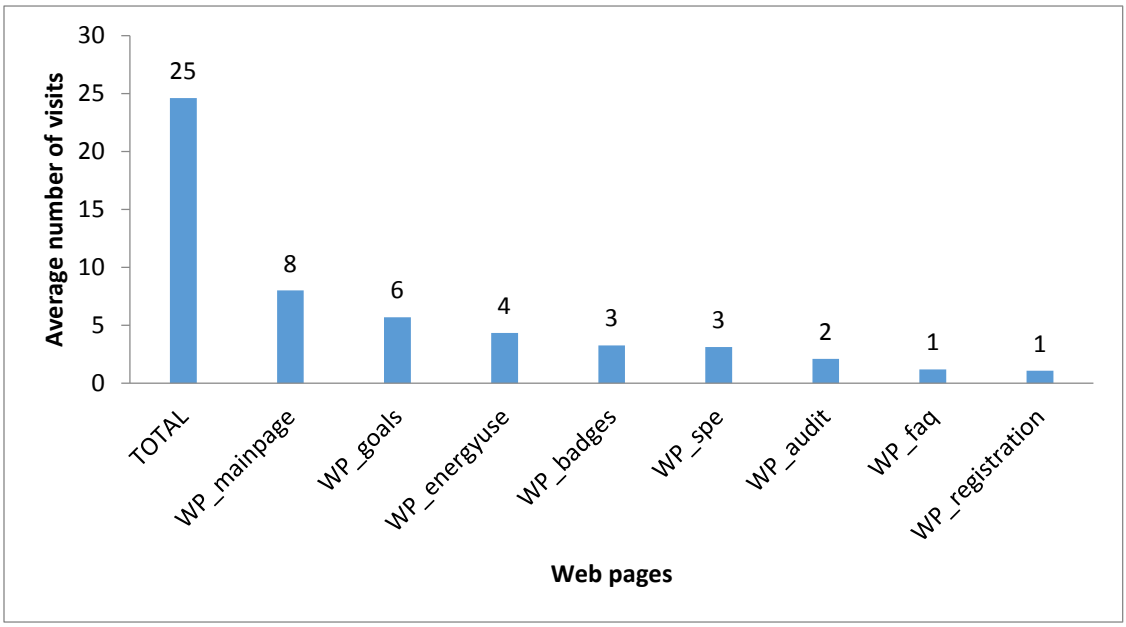
Note: DR Event duration was 1-4 pm on 7/16/13.

Web Portal Use

A total of 296 views of the web portal were recorded during the intervention period. The mean number of log-ins to the portal was 8, and the mean number of views of any page within the portal was 25. A one-way ANOVA did not find significant differences in the number of portal log-ins by group (Basic = 26, Enhanced=27; F (1, 31) = 0.003, p<.96). The most visited page was the goals page, which is not surprising given the bimonthly reminders to check in to the goals page. The next most commonly visited page was energy use, followed by badges. See Figure 10 below for a visual representation of findings.

Examining the number of log-ins to the goals page specifically, the mean number of log-ins among the sample was approximately 6. A one-way ANOVA did not find significant differences in number of visits between Basic and Enhanced users (F (1, 31) = 0.61, p<.44). However, results were in the expected direction, with Basic users checking the goals page an average of 5 times and Enhanced users an average of 7 times.

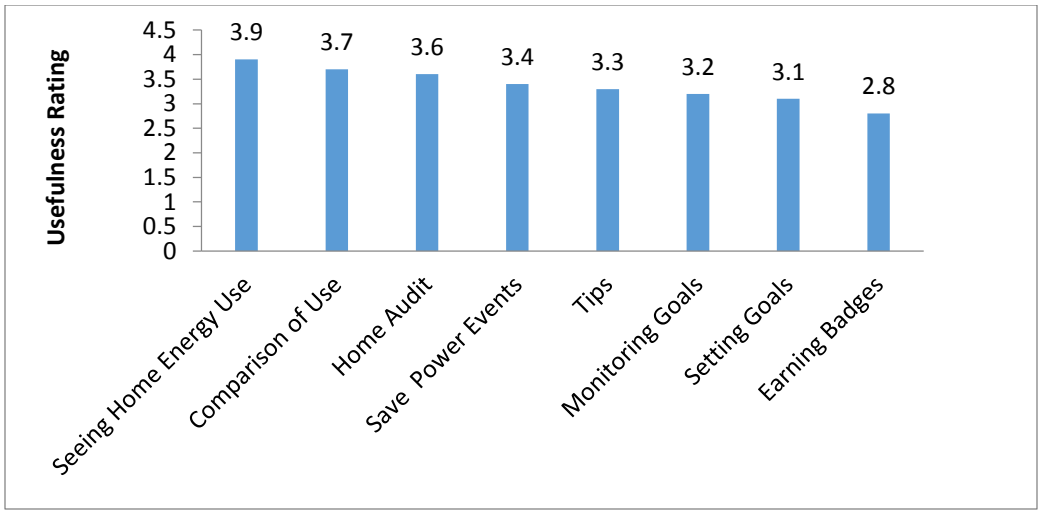
Figure 10. Mean Number Of Web Page Visits.



Participant Experience Ratings

Participants rated nearly all of the web tools as at least somewhat useful, including home energy use and comparisons, home audit, save power events, goal setting, and goal monitoring. Badge earning had the lowest utility rating. Overall, Enhanced participants reported higher usefulness ratings than did Basic users, except for setting goals and earning badges. See Figures 11 and 12 below for details. Note that because few participants completed the follow-up survey, it is likely that this subgroup is not representative of the entire sample of study participants, so results should be interpreted with caution.

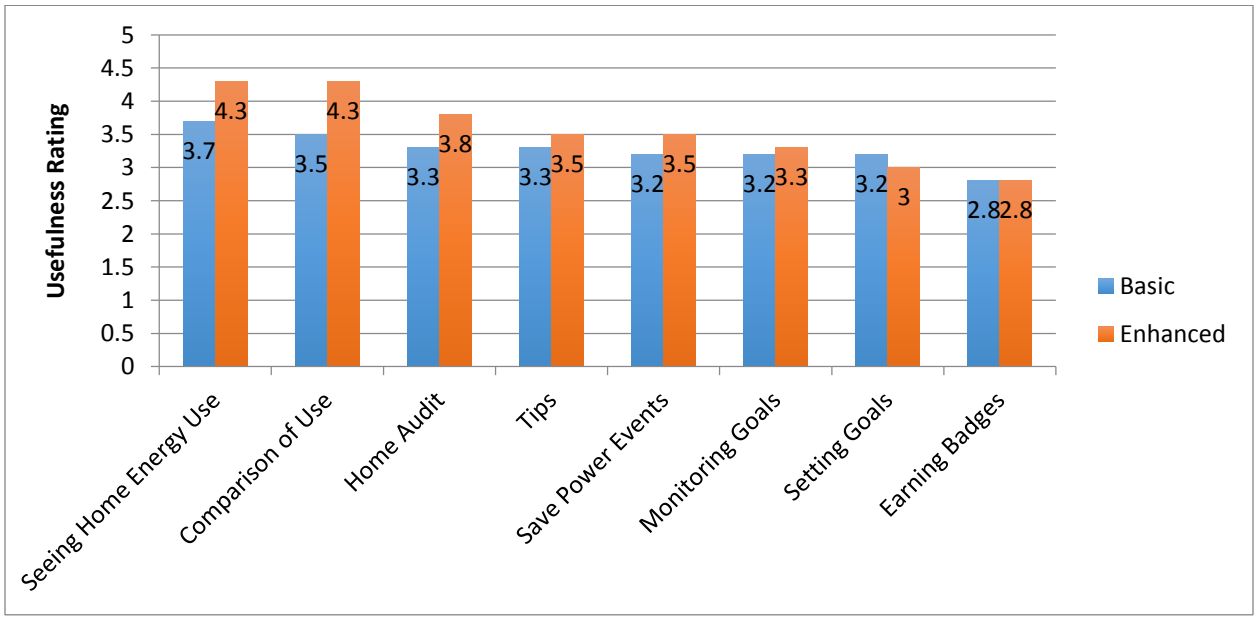
Figure 11. Web Portal Usefulness Ratings.



Note: Results are based on n = 10 participants who completed follow-up survey.

Usefulness was rated on a scale from 1 (Very Useless) to 5 (Very Useful).

Figure 12. Web Portal Usefulness Ratings By Group.



Note: A total of 10 participants (n_{basic} = 6; $n_{enhanced}$ = 4) completed follow-up survey.

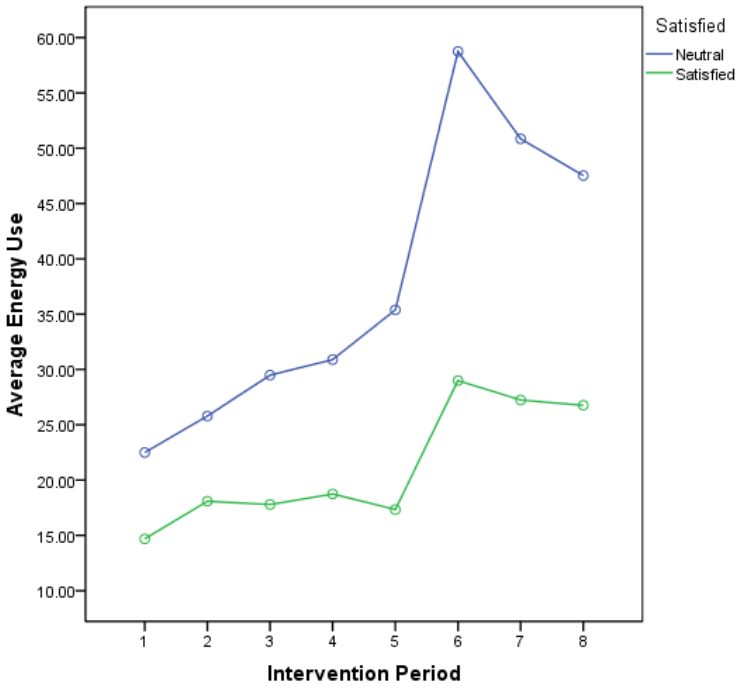
Usefulness was rated on a scale from 1 (Very Useless) to 5 (Very Useful).

Among the 10 participants who responded to the follow-up survey, 6 were satisfied with the program, 3 were neutral, and only 1 was dissatisfied. A similar pattern was found for level of satisfaction with energy

management tools. Additionally, 7 of 10 participants said they learned new things about energy use and energy management.

We also examined the relationship between energy use and participant satisfaction with SmartPower Partners Program as shown in Figure 13. Findings suggest that satisfied participants also tended to use less energy. Accordingly, energy efficiency and DR programs that are closely matched to meet customer preferences may hold more promise for success than programs customers are not fond of. However, the small sample size suggests that results should be interpreted with caution.

Figure 13. Participant Satisfaction By Mean Daily Energy Usage (n = 12).



7. Summary of the major findings and conclusions including lessons learned and best practices.

The goal of the present study was to develop and implement a behavioral intervention to promote energy conservation and load curtailment during demand response events. An additional objective of the study was to evaluate the relative effectiveness of two different goal-setting techniques on energy conservation. As part of the study, a total of 49 Los Angeles Department of Water and Power

residential customers located in the Northridge, CA area in Summer 2013 participated in the study. The customized website was built to deliver the intervention, which included a number of techniques that have received empirical support for reducing energy use, most notably goal-setting and historical and normative energy feedback. Participants were randomly assigned to 1of 2 experimental groups. In the Simple Goal condition, participants set an energy reduction goal (e.g., reduce home energy use by 10%) for the subsequent two weeks. In the Enhanced Goal condition, participants not only set an energy reduction goal, but were also guided through a process whereby they selected from among a list of behaviors that they agreed to perform in order to achieve their goal. Several weeks later, all participants were contacted and asked to log in to the website to check whether they had achieved their goals.

We examined energy use during participants' first goal periods, when engagement levels were likely to be highest. During initial goals periods, use declined by 0.80% across the sample. Basic users increased by 5.90%, whereas Enhanced users decreased by 7.48% on average. Examining energy use across the 3-month intervention period, these results were not sustained: participants used 29% more electricity during the intervention relative to baseline. There were no group differences observed in this overall rate of change. It is possible that the intervention may simply have effects that are short in duration, which is common to many behavioral interventions. The process of making initial behavioral changes is different from maintaining change over longer periods of time. An alternate intervention tool, or booster sessions, may be needed to successfully sustain behavioral changes over time.

In addition to general conservation, participants were also asked to take part in a total of 3 Demand Response (DR) events. Usage during DR events was 10-35% lower than usage during temperature-matched non-DR days. Examining DR results by group, usage among Enhanced users was significantly lower than that among Basic users during the first 2 events. There were no group differences for the 3rd DR event. The fact that Enhanced users performed better than Basic users during DR events 1 and 2 suggests that the action planning step required of Enhanced users may have made energy saving more salient in general, and contributed to the observed group differences. The fact that the intervention had a positive impact on participation in DR events on days that had peak temperatures lower than 85F, but not on hotter days suggests that extreme heat may be a barrier to DR participation. It is possible that a temperature threshold exists above which any behavioral changes are unlikely to occur. Identifying motivators for participation under such conditions should be a focus of future research so that alternate measures to encourage DR participation can be identified. Alternatively, likelihood of DR participation may vary by day of week: DR events 1 and 2 occurred on Sundays, whereas the 3rd event took place on a Tuesday. Flexibility in energy use activities may be greater on weekends relative to weekdays.

Examining website usage, users logged into the portal an average of 8 times. The most commonly visited page was the goals page, which is not surprising given the bimonthly reminders to check in to the goals page. The next most commonly visited page was energy use, followed by badges. Examining the number of log-ins to the goals page specifically, the mean number of log-ins among the sample was approximately 6, with Basic users checking the goals page an average of 5 times and Enhanced users an average of 7 times. Although this difference was not statistically significant, in light of the superior performance of Enhanced users relative to Basic users for energy consumption during the first 2 DR events and initial goal periods, it is possible that exposure or engagement mediated the relationship between study group and these outcomes.

In terms of program satisfaction, among the 10 participants who responded to the follow-up survey, 6 were satisfied with the program, 3 were neutral, and only 1 was dissatisfied. A similar pattern was found for level of satisfaction with energy management tools. Participants rated nearly all of the web tools as at least somewhat useful, with home energy use rated highest and badge earning rated lowest. Additionally, 7 of 10 participants also said they learned new things about energy use and energy management. The web usage data point to the energy usage, goals, and Save Power Events pages as the most valuable tools in the program.

Lessons Learned

A number of lessons were learned in the design, implementation and evaluation of this study. Based on these, we have made several recommendations for streamlining and improving future projects:

- Take proactive steps to avoid attrition
    - Attrition is a limitation of any longitudinal study. The initial sample size recruited should be large enough to account for expected attrition rates. In addition, measures should be taken to minimize the time between initial recruitment and program launch, which contributed to high attrition rates for the present study. The actual launch date was approximately 1 year after the planned launch date. Consequently, a number of participants expressed that they were no longer interested or were annoyed that the start date had been changed numerous times. Requisite partnerships within and/or between institutions should be in place prior to subject recruitment. Delays in identifying the appropriate contacts in rates added to the delay. When unforeseen delays occur, increasing personal contact with participants may reduce attrition. Although participants in the present study received regular emails from the study team during delay periods, these messages may have been missed by participants, or perhaps were not salient enough to retain participants' interest in the study. Project teams should plan carefully for the possibility of delays, and allot adequate time and resources to place personal calls to study participants if necessary.
- Select optimal timing to observe a reduction
    - Due to delays, the present study launched in Spring, before warmer Summer temperatures and correspondingly high energy consumption. Typical energy use patterns should be examined before planning intervention time periods. Time frames where usage tends to increase should be avoided, such as Spring/Summer in southern California.
- Well-organized datasets require early team collaboration
    - The final dataset for this project combined nearly 10 smaller databases. This was due to different information systems collecting the survey, web portal usage, and energy data. Nonetheless, matching participant data across files was a time consuming process, in part because not all files shared the same participant identifiers. To the extent possible, collection files should be minimized. In addition, files should have consistent identifiers across files. Facilitating this requires collaborative efforts by the team early in project planning, before databases are created.
- Talking to participants goes a long way
    - Several participants called the research staff to ask questions about various topics. Productive conversations with these individuals appeared to lead to higher retention rates. For instance, one customer had concerns about a spuriously high bill, and the project team was able to connect the participant with the appropriate team at LADWP to resolve the issue. Although initially displeased due to the high bill, the participant continued to take part in the study.

- Evaluate the value of incentives
    - Incentives can be effective for encouraging study participation when they are valued by the target population. However, they are also often costly, and when the participants are not interested, resources may be better invested elsewhere.
- Shorten survey length
    - Many users only partially completed the baseline and follow-up surveys, which were relatively long. In the future, surveys should be brief and focused to promote completion. Additionally, randomizing the order of item presentation would assist in rounding out data coverage, especially where imputation methods are available.
- Simplify web portal
    - Based on number of visits to each web page, certain web pages appeared to be more valued by participants more than others. Project teams should take this into consideration to assist with resource allocation.

8. Summary of future plans and next steps with respect to additional testing, demonstration, or deployment

Based on the foregoing findings, the web portal will undergo revision and refinement in preparation for re-launch to all SGRDP customers during Operations. The lessons learned from the present project have directly informed the design, functionality, and customer engagement procedures that will be used during Operations. For instance, efforts will be made to minimize any potential delays between recruitment and project launch, as this led to attrition in the present project. Additionally, certain web portal modules that were not visited frequently during the pre-operations period will not be made available during Operations. Instead, resources will be directed towards refining and improving modules that received heavy traffic and high utility ratings, as the latter are more likely to be used by demonstration customers.

9. Appendices

Appendix A: Recruitment letter







Dear XX Household,

LADWP, USC, UCLA, and the NASA Jet Propulsion Laboratory have come together to invite you to experience a new home energy management technology as part of the SmartPower Partners Program. Other utilities, such as Southern California Edison and Glendale Water and Power, are already providing their customers with similar types of services. LADWP is inviting a limited number of customers to try out these tools completely free of charge before releasing them to additional customers. Your household was selected based on geographic and technical requirements related to the City's electric distribution system.

If you decide to participate, LADWP will replace your current electric meter with a "smart" meter. This meter will function similarly to your current meter, except that it will make information on your household's electricity usage more readily available to you. As a SmartPower Partner, you will:

- Be granted access to cutting-edge home energy management tools and services at no cost to you.
- Be able to monitor your home energy use on the internet in near real-time, which will help you manage your usage and could result in lowering your bill

If you participate, all costs associated with the meter and installation will be covered by LADWP. Your electricity billing rate plan will not change.

Participation in this project is limited, so if you are interested, please apply for a slot by **April 1, 2012**. To sign up to be SmartPower Partner or to obtain more information, you may do any of following:

1. Type this link into any internet browser: www.LADWPSmartPowerPartners.com (or)
2. Call 213.367.0152 to speak with a project team member (or)
3. Email SmartPowerPartners@ladwp.com (or)
4. Fill out your information on the enclosed postage-paid postcard

The SmartPower Partners Program is part of the Los Angeles Smart Grid Regional Demonstration Program, the goals of which are to improve overall reliability of electricity services and offer additional methods for energy management. This will make LADWP's electricity services more efficient, assist in predicting and avoiding power outages, and provide customers with new options for managing home energy bills.

We thank you in advance for signing up for this exciting partnership in energy savings by contacting us soon and joining us as a SmartPower Partner!

Your partners in energy efficiency,

The SmartPower Partners Team

Appendix B: Eligibility Survey

Thank you for your interest in the LADWP SmartPower Partners Program! LADWP, USC, UCLA and the NASA Jet Propulsion Laboratory have joined forces to offer this program. Please respond to the questions below so we can determine your eligibility to participate.

My home electricity provider is the Los Angeles Department of Water & Power (LADWP).

- ❍ Yes (1)
- ❍ No (2)

If No Is Selected, Then Skip To End of Survey

Do you have "My Account" set up on the LADWP website?

- ❍ Yes (1)
- ❍ No (2)
- ❍ I don't know (3)

What is the address of your primary place of residence? This information will be used to verify eligibility and will remain confidential.

Street address (e.g., 123 Main St. Apt 3) (1)
City (2)
ZIP (3)

For how many years have you lived at this address?

Do you have plans to move from this address before January 2013?

- ❍ Yes (1)
- ❍ No (2)

If Yes Is Selected, Then Skip To End of Survey

What is your LADWP Customer Access Number (CAN)? We will use this information to verify that the residence under your account is eligible for the SmartPower Partners Program. You can find your 10-digit CAN in the upper left-hand corner of your bill.

In what year were you born?

If In what year were you born? Is Greater Than or Equal to 1995, Then Skip To End of Survey

How often do you use the following?

	N/A - I don't have access to this device/service (1)	Never (2)	Less than Once a Month (3)	Once a Month (4)	2-3 Times a Month (5)	Once a Week (6)	2-3 Times a Week (7)	Daily (8)
Internet on computer at my home (1)	❍	❍	❍	❍	❍	❍	❍	❍
Internet on computer at my place of work (2)	❍	❍	❍	❍	❍	❍	❍	❍
Internet browser on my smart phone (3)	❍	❍	❍	❍	❍	❍	❍	❍
Internet browser on my tablet device (e.g., iPad) (4)	❍	❍	❍	❍	❍	❍	❍	❍
Basic cell phone without internet access (5)	❍	❍	❍	❍	❍	❍	❍	❍
Mobile	❍	❍	❍	❍	❍	❍	❍	❍

phone "apps" (6)								

Would you be willing to log into the LADWP website weekly in order to access the new energy management tools available during the program?

- ❍ Yes (1)
- ❍ No (2)

If No Is Selected, Then Skip To End of Survey

One part of the SmartPower Partners Program will be Save Power Events. Save Power Events work like this: you would be notified by text, automated phone call, or email the day before a Save Power Event is scheduled. You would be alerted again a few hours prior to the Event, and asked to conserve power in your home for a few hours by taking any action of your choice: you may choose to turn down thermostat by a few degrees, avoid running washing machines/dryers, or engage in other energy-saving behaviors during the event. Are you willing to participate in at least one Save Power Event during the SmartPower Partners Program?

- ❍ Yes (1)
- ❍ No (2)

If No Is Selected, Then Skip To End of Survey

Thank you for completing the SmartPower Partners eligibility questionnaire. We will contact you to let you know if you are eligible to participate. Please provide your contact information below. Your information will only be accessible to the study team.

Home phone (1)
Cell phone (2)
Email address (3)

Appendix C: Baseline Survey

The SmartPower Partners program is a joint effort between LADWP, USC, UCLA and JPL. Together, we will work to understand which energy management tools work best for whom. Integrating research into the project ensures that we will have better information to improve services offered to LADWP

customers. Please join other LADWP customers in responding to the below questions to help with our research efforts.

What is your gender?

- ❍ Male (1)
- ❍ Female (2)

With which ethnic category do you most strongly identify?

- ❍ African or African American (1)
- ❍ Asian or Asian American (2)
- ❍ Caucasian/white (3)
- ❍ Latino/a (4)
- ❍ Native American or Pacific Islander (5)
- ❍ Multiracial (6)
- ❍ Other (please specify) (7) _____

What is the primary language you speak at home?

- ❍ Armenian (1)
- ❍ Cantonese (2)
- ❍ English (3)
- ❍ Hindi (4)
- ❍ Japanese (5)
- ❍ Korean (6)
- ❍ Mandarin (7)
- ❍ Spanish (8)
- ❍ Russian (9)
- ❍ Tagalog (10)
- ❍ Vietnamese (11)
- ❍ Other (please specify) (12) _____

Many questions below refer to your residence. If you have multiple residences, please respond only for your primary residence at which LADWP is your electricity provider.

Including you, how many people live in your household?

	0 (1)	1 (2)	2 (3)	3 (4)	4 (5)	5 (6)	6 (7)	7 (8)	8 (9)	9 (10)	10+ (11)
Children (under age 18) (1)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Adults (2)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍

How would you describe your residence?

- ❍ Single family home (detached or free-standing residence) (1)
- ❍ Multi-family home (apartment, condo) (2)
- ❍ Duplex, triplex, or 4-plex (3)
- ❍ Townhouse (4)
- ❍ Mobile home (5)
- ❍ Other (please specify) (6) _____

Do you own or rent this residence?

- ❍ Own (1)
- ❍ Rent (2)
- ❍ Other (please specify) (3) _____

What is your marital status?

- ❍ Never married (1)
- ❍ Currently married (2)
- ❍ Currently in a domestic partnership (3)
- ❍ Divorced (4)
- ❍ Widowed (5)
- ❍ Separated (6)
- ❍ Prefer not to answer (7)

What is the highest level of schooling that you have completed?

- ❍ Less than high school (1)
- ❍ High school / GED (2)
- ❍ Technical or trade school (3)
- ❍ Some college or Associate's degree (4)
- ❍ 4-year college graduate (5)
- ❍ Completed graduate school or professional degree program (6)

Please provide your date of birth and first and last initials. We remind you that your responses are confidential. We ask for your birthdate and initials because we may request your participation in a future survey. By providing this information, you enable us to create a code to link your response from this survey with responses to a future survey. We respect your privacy, and your responses will only be accessible to the study team.

Birthdate (MM/DD/YYYY)? EX: September 18, 1972 = 09/18/1972. (1)

Initials (first and last name only)? EX: John Doe = JD. If you have multiple names, please provide the first letter of your first name and the first letter of your last name. EX: Maria Eugenia Alvarez Garcia = MA (2)

What is your annual household income?

- ❍ Under $25,000 (1)
- ❍ $25,000 - $50,000 (2)
- ❍ $50,001-$75,000 (3)
- ❍ $75,001-$100,000 (4)
- ❍ More than $100,000 (5)
- ❍ Prefer not to answer (6)

What do you consider to be your political orientation?

- ❍ Very liberal (1)
- ❍ Liberal (2)
- ❍ Somewhat liberal (3)
- ❍ Moderate (4)
- ❍ Somewhat conservative (5)
- ❍ Conservative (6)
- ❍ Very conservative (7)

Who in your household is responsible for paying your electric bill (check all that apply)?

- ❑ You (1)
- ❑ Spouse or partner (2)
- ❑ Roommate (3)
- ❑ Parent or grandparent (4)
- ❑ Child or grandchild (5)
- ❑ Landlord or building management (6)
- ❑ Boss (7)
- ❑ Other (please specify) (8) _____

When it comes to how energy is used in your home (for example, how high or low to set the heating and cooling, or when to turn lights off), how are decisions generally made?

- ❍ I decide (1)
- ❍ Somebody else decides (please specify) (2) _____
- ❍ We make a decision jointly (3)
- ❍ We try to compromise on what to do but have some differences of opinion about these matters (4)

How often do you do the following?

	Never (1)	Less than Once a Month (2)	Once a Month (3)	2-3 Times a Month (4)	Once a Week (5)	2-3 Times a Week (6)	Daily (7)
Search for things online/ on the internet (1)	❍	❍	❍	❍	❍	❍	❍
Check email on a computer (2)	❍	❍	❍	❍	❍	❍	❍
Check email on my mobile phone (3)	❍	❍	❍	❍	❍	❍	❍
Check email on my tablet device (e.g., iPad) (4)	❍	❍	❍	❍	❍	❍	❍
Send or receive text messages on my mobile phone (5)	❍	❍	❍	❍	❍	❍	❍
Use Facebook (6)	❍	❍	❍	❍	❍	❍	❍

Use Twitter (7)	❍	❍	❍	❍	❍	❍	❍
Check out videos on YouTube (8)	❍	❍	❍	❍	❍	❍	❍
Read or write Blogs (9)	❍	❍	❍	❍	❍	❍	❍
Use other internet-based service (please specify) (10)	❍	❍	❍	❍	❍	❍	❍

Have you participated in any of the following programs through LADWP in the past 5 years?

	Yes (1)	No (2)
Green Power Program (1)	❍	❍
Electric Vehicle Program / Electric Vehicle Charger Rebate (2)	❍	❍
Low Income Weatherization (3)	❍	❍
Low Income Refrigerator Replacement Program (4)	❍	❍
RETIRE Program (5)	❍	❍
Energy Upgrade California (6)	❍	❍
Solar Incentive Program (7)	❍	❍
Time Of Use (TOU) Rate (8)	❍	❍
Other energy efficiency program (please specify) (9)	❍	❍

SmartPower Partners are in the unique position to shape future service offerings at LADWP. Therefore, Partners' feedback and input on the program is critical. For this reason, LADWP would like to contact SmartPower Partners during the program (June 2012-December 2012). Contacts will be made primarily by mobile phone texts and by email. For instance, you may receive an email requesting that you follow a link to a brief on-line survey that asks you what's working and what could be improved about the program. As another example, you may receive a text alert to check your Web Portal. What frequency of contact would be ideal for you?

- ❍ Daily (1)
- ❍ A few times per week (2)
- ❍ Once per week (3)
- ❍ Twice per week (4)
- ❍ Monthly (5)
- ❍ Twice per month (6)

What is your overall attitude toward LADWP?

- ❍ Very Negative (1)
- ❍ Negative (2)
- ❍ Somewhat Negative (3)
- ❍ Neutral (4)
- ❍ Somewhat Positive (5)
- ❍ Positive (6)
- ❍ Very Positive (7)

How satisfied are you with the current home energy management options provided to you by LADWP?

- ❍ Very Dissatisfied (1)
- ❍ Dissatisfied (2)
- ❍ Somewhat Dissatisfied (3)
- ❍ Neutral (4)
- ❍ Somewhat Satisfied (5)
- ❍ Satisfied (6)
- ❍ Very Satisfied (7)

If you tried to conserve electricity in your home, by what percentage do you think you could reduce your home electricity consumption in a given month, compared to recent months?

% (1)

In the future, LADWP would like to provide all of its customers with a free energy management service that lets you see how much electricity is being used in your home, in almost real time, and gives you tips to help you save energy and money. This free service may be provided using one of several methods, such as a web site, a smart phone "app", or a display that can be installed inside of your home. Which home energy management method appeals most to you (choose one)?

- ❍ A free web site (please indicate your reasoning) (1) _____
- ❍ A free smartphone app (please indicate your reasoning) (2) _____
- ❍ A free in-home display (please indicate your reasoning) (3) _____
- ❍ Other (please specify) (4) _____
- ❍ None of these options would appeal to me (please indicate your reasoning) (5) _____

The best ways to reach me with information about home energy saving programs are (CHOOSE THREE):

- ❑ Put stories in the media (newspaper, radio, TV) (1)
- ❑ Post the information on my electric company's web site (2)
- ❑ Put the information on a hangtag on my door (3)
- ❑ Include information about them with my bill (4)
- ❑ Call me at home/leave a message (5)
- ❑ Invite me to "Like" my electric company's page on Facebook (6)
- ❑ Call me on my cell phone/leave a message (7)
- ❑ Invite me to follow my electric company on Twitter. (8)
- ❑ Send me a text message (9)
- ❑ Have speakers come to my community to talk about it (10)
- ❑ Send me an email (11)
- ❑ OTHER (Please specify) (12) _____

How would you rate your knowledge of "Smart Meters"?

- ❍ I have never heard about them (1)
- ❍ I don't know much about them (2)
- ❍ I know a little bit about them (3)
- ❍ I know a good deal about them (4)
- ❍ I know a lot about them (5)

In your own words, what is a smart meter? What you like about them? What don't you like about them?

What is your general opinion of Smart Meters?

- ❍ Very negative (1)
- ❍ Negative (2)
- ❍ Somewhat negative (3)
- ❍ Neutral (4)
- ❍ Somewhat positive (5)
- ❍ Positive (6)
- ❍ Very positive (7)
- ❍ I don't know enough about them to give an opinion (8)

"Smart grid" refers to technology being used to bring electricity delivery systems into the 21st century, using computer-based remote control and automation. Two-way communication technology and computer processing that have been used for decades in other industries makes these systems possible. They offer many benefits to utilities and consumers, including improved energy efficiency on the electricity grid and in utility customers' homes and offices (US Department of Energy, 2012).

Please check all that apply.

- ❑ I know someone who has a smart meter. (1)
- ❑ I have spoken to someone who has a smart meter about smart meters and / or smart grid. (2)
- ❑ I have spoken to someone who does not have a smart meter about smart meters and / or smart grid. (3)

Answer If Please check all that apply. I have spoken to someone who has a smart meter about smart meters and / or smart grid. Is Selected Or Please check all that apply. I have spoken to someone who does not have a smart meter about smart meters and / or smart grid. Is Selected

smopf You indicated that you have discussed Smart Meters with others. What were the key points of the conversation? What were other people's opinions of Smart Meters?

Which of the following benefits of investing in a "smart grid" would be most important to you personally?

	Not at all Important (1)	Very Unimportant (2)	Somewhat Unimportant (3)	Somewhat Important (4)	Very Important (5)	Extremely Important (6)
Making our electrical system more efficient (1)	❍	❍	❍	❍	❍	❍
Reducing our dependence on fossil fuels (2)	❍	❍	❍	❍	❍	❍
Improving our aging electric infrastructure (3)	❍	❍	❍	❍	❍	❍
Greater choice in how much I pay for electricity (4)	❍	❍	❍	❍	❍	❍
Greater control over my electric bill (5)	❍	❍	❍	❍	❍	❍
Improving resilience against attack and natural disaster (6)	❍	❍	❍	❍	❍	❍
Fostering economic growth and	❍	❍	❍	❍	❍	❍

creating jobs (7)						
Better integration of renewable sources of electricity (e.g., solar) (8)	❍	❍	❍	❍	❍	❍
Ability to support a growing number of plug-in electric vehicles (9)	❍	❍	❍	❍	❍	❍
More reliable electric power (e.g., fewer blackouts) (10)	❍	❍	❍	❍	❍	❍
Greater choice of when to purchase and use electricity (11)	❍	❍	❍	❍	❍	❍
Reducing greenhouse gas emissions and protecting the environment	❍	❍	❍	❍	❍	❍

(12) Better information about my home energy use (13)	❍	❍	❍	❍	❍	❍

Energy use relates to many broader issues and parts of daily life. Think about the following statements in relation to energy efficiency. Rank the top five statements that are most important to you by dragging and dropping. I am motivated to do my part in terms of energy efficiency because:

_____ It could promote United States energy security / independence (not relying on foreign production) (1)
_____ My family could benefit (2)
_____ It aligns with my religious values (3)
_____ Environmental quality (local and/or global) could benefit (4)
_____ My health and/ or the health of other people could benefit (5)
_____ My economic well-being could improve (6)
_____ The well-being of the economy at large could improve (7)
_____ My friends, family members, or colleagues would like it if I did (8)
_____ My friends, family members, or colleagues engage in energy-efficient behaviors (9)
_____ My quality of life could improve (10)
_____ It is the right thing to do (11)
_____ Other (please specify) (12)

Please indicate the extent to which you agree or disagree with each of the following statements, using the scale provided.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
I tend to know about new ways to save energy before most other people do. (1)	❍	❍	❍	❍	❍	❍	❍
If I heard about a new way to save energy, I would be interested enough to check it out. (2)	❍	❍	❍	❍	❍	❍	❍
I try to buy energy efficient household appliances. (3)	❍	❍	❍	❍	❍	❍	❍
I try to use appliances like my clothes dryer or dishwasher relatively early in the morning or late in the evening for energy efficiency and/or financial reasons. (4)	❍	❍	❍	❍	❍	❍	❍
I tend to start using new technologies/devices before most other people. (5)	❍	❍	❍	❍	❍	❍	❍
People in my social environment (family, friends, coworkers, etc)	❍	❍	❍	❍	❍	❍	❍

make me feel that I should adopt certain energy-saving behaviors. (6)							
Higher energy bills would put a big dent in my financial resources. (7)	❍	❍	❍	❍	❍	❍	❍
Every citizen must take responsibility for conserving energy. (8)	❍	❍	❍	❍	❍	❍	❍
Energy efficiency is important to me. (9)	❍	❍	❍	❍	❍	❍	❍
Energy conservation is important to me. (10)	❍	❍	❍	❍	❍	❍	❍
I watch my energy use habits to make sure I'm not wasting energy. (11)	❍	❍	❍	❍	❍	❍	❍
I specifically look for energy-efficient versions of appliances and/or products. (12)	❍	❍	❍	❍	❍	❍	❍

Please rate the extent to which you agree or disagree with each of the following statements.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neutral (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
I often feel a strong connection to nature. (1)	❍	❍	❍	❍	❍	❍	❍
I think of nature as a family that I belong to. (2)	❍	❍	❍	❍	❍	❍	❍
I see myself as a part of the greater circle of life. (3)	❍	❍	❍	❍	❍	❍	❍
Humans are more important than plants and animals. (4)	❍	❍	❍	❍	❍	❍	❍
I feel related to animals and plants. (5)	❍	❍	❍	❍	❍	❍	❍
I feel I belong to the Earth and that the Earth belongs to	❍	❍	❍	❍	❍	❍	❍

me. (6) I feel that all living things in this world are connected, and I am a part of that. (7)	❍	❍	❍	❍	❍	❍	❍
There is something that every living thing shares. (8)	❍	❍	❍	❍	❍	❍	❍
Like the tree in the forest, I feel I belong to nature. (9)	❍	❍	❍	❍	❍	❍	❍
I don't feel part of nature. (10)	❍	❍	❍	❍	❍	❍	❍

Participating in energy efficiency is difficult for me due to...

	Strongly Disagree (1)	Disagree (2)	Neither Agree nor Disagree (3)	Agree (4)	Strongly Agree (5)
The physical construction of my residence (1)	❍	❍	❍	❍	❍
The up-front costs of energy-efficient investments or repairs (2)	❍	❍	❍	❍	❍
The age of my home (3)	❍	❍	❍	❍	❍
Lack of time (4)	❍	❍	❍	❍	❍
I'm not sure what to do (5)	❍	❍	❍	❍	❍
I don't think I have the required technical experience (6)	❍	❍	❍	❍	❍
I do not know where to get information (7)	❍	❍	❍	❍	❍
My family's medical issues (8)	❍	❍	❍	❍	❍
A lack of cooperation	❍	❍	❍	❍	❍

of others in my residence (9) Other (please specify) (10)	❍	❍	❍	❍	❍

Appendix D: DR Survey

Please provide your LADWP service address.

Street Address (e.g., 123 Main St., Apt. 3) (1)
City (2)
ZIP (3)

Which of the following do you have in your home?

- ❑ Central air conditioning (1)
- ❑ Central heat (2)
- ❑ Wall or window air conditioning unit (3)
- ❑ Electric space heater (4)

Did you participate in the Save Power Event on Sunday 5/19/2013?

- ❍ Yes (1)
- ❍ No (2)

Answer If Did you participate in the Save Power Event on [date]? No Is Selected

Why didn't you participate? (Choose all that apply)

- ❑ I didn't know it was happening (1)
- ❑ I received the notification too late and couldn't take the appropriate actions (2)
- ❑ I was entertaining others in my residence (3)
- ❑ I didn't want to be uncomfortable (4)
- ❑ It might have been inconvenient to participate (5)
- ❑ I wasn't sure what actions to take (6)
- ❑ I didn't think any actions I could take would have made a contribution (7)
- ❑ It was not important to me to participate (8)
- ❑ Other (please specify) (9) _____

If I didn't know it was happening Is Displayed, Then Skip To End of Survey

Answer If Which of the following do you have in your home? Central air conditioning Is Selected Or Which of the following do you have in your home? Central heat Is Selected

What adjustments, if any, did you make to your home's central heating / cooling system during the Event with the intention of saving energy? Please write "off" in the box if your thermostat was turned off.

	Degrees Fahrenheit (1)
Before the event, my thermostat was set to (1)	
During the event, I adjusted it to (2)	

Answer If Which of the following do you have in your home? Wall or window air conditioning unit Is Selected

What adjustments, if any, did you make to your air conditioning unit during the Event with the intention of saving energy?

	Low (1)	Medium (2)	High (3)	Off (4)
Before the event, my air conditioning unit was set to (1)	❍	❍	❍	❍
During the event, I adjusted it to (2)	❍	❍	❍	❍

Answer If Which of the following do you have in your home? Electric space heater Is Selected

What adjustments, if any, did you make to your electric space heater during the Event with the intention of saving energy?

	Low (1)	Medium (2)	High (3)	Off (4)
Before the event, my electric space heater was set to (1)	❍	❍	❍	❍
During the event, I adjusted it to (2)	❍	❍	❍	❍

Answer If Did you participate in the Save Power Event on [date]? Yes Is Selected

What other actions did you take during the Event with the intention of saving energy? Please select all that apply.

- ❑ Refrained from using washing machine (1)
- ❑ Washed fewer loads of clothes in washing machine than I had planned (2)
- ❑ Refrained from using clothes dryer (3)
- ❑ Used a low-power setting to dry my clothes in the clothes dryer (4)
- ❑ Refrained from using dishwasher (5)
- ❑ Did fewer loads of dishes in dishwasher than I had planned (6)
- ❑ Refrained from using electric oven / stove (7)
- ❑ Refrained from ironing clothes (8)
- ❑ Refrained from using vacuum cleaner (9)
- ❑ Turned off lights that were not in use (10)
- ❑ Unplugged appliances (e.g., TV, coffee maker, microwave, gaming console) that were not in use (11)
- ❑ Refrained from charging my plug-in electric vehicle (12)
- ❑ Turned off pool pump (13)
- ❑ Turned off jacuzzi (14)
- ❑ Turned off sprinkler system (15)
- ❑ Turned off / unplugged outdoor fountain (16)
- ❑ Left my residence (17)
- ❑ Other (please specify) (18) _____

Answer If Did you participate in the Save Power Event on Sunday 5/1... Yes Is Selected

Rate your level of physical comfort during the Event.

- ❍ Very uncomfortable (1)
- ❍ Slightly uncomfortable (2)
- ❍ Neutral (3)
- ❍ Slightly comfortable (4)
- ❍ Very comfortable (5)

How likely are you to participate in a future Save Power Event?

- ❍ Very Unlikely (1)
- ❍ Unlikely (2)
- ❍ Somewhat Unlikely (3)
- ❍ Undecided (4)
- ❍ Somewhat Likely (5)
- ❍ Likely (6)
- ❍ Very Likely (7)

Answer If Did you participate in the Save Power Event on [date]? Yes Is Selected

Why did you participate? (select all that apply)

- ❑ Other people I know were participating. (1)
- ❑ Other people I know made me think it was mandatory. (2)
- ❑ I thought it was a great idea. (3)
- ❑ I feel strongly about energy conservation. (4)
- ❑ Other (please specify) (5) _____

You can unlock a badge for completing Save Power Event surveys! The completion code word for this survey is: POWER

To unlock your badge, please go to the Save Power Event leaf in your SmartPower Partners portal and enter the above code word in the box provided.

Appendix E: Follow-up Survey

What is the address of your primary place of residence? This information will be used to verify eligibility and will remain confidential.

Street address (e.g., 123 Main St. Apt 3) (1)
City (2)
ZIP (3)

Many questions below refer to your residence. If you have multiple residences, please respond only for your primary residence at which LADWP is your electricity provider.

Including you, how many people live in your household?

	0 (1)	1 (2)	2 (3)	3 (4)	4 (5)	5 (6)	6 (7)	7 (8)	8 (9)	9 (10)	10+ (11)
Children (under age 18) (1)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Adults (2)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍

Who in your household is responsible for paying your electric bill (check all that apply)?

- ❑ You (1)
- ❑ Spouse or partner (2)
- ❑ Roommate (3)
- ❑ Parent or grandparent (4)
- ❑ Child or grandchild (5)
- ❑ Landlord or building management (6)
- ❑ Boss (7)
- ❑ Other (please specify) (8) _____

When it comes to how energy is used in your home (for example, how high or low to set the heating and cooling, or when to turn lights off), how are decisions generally made?

- ❍ I decide (1)
- ❍ Somebody else decides (please specify) (2) _____
- ❍ We make a decision jointly (3)
- ❍ We try to compromise on what to do but have some differences of opinion about these matters (4)

Please provide your date of birth and first and last initials. We remind you that your responses are confidential. We ask for your birthdate and initials because we may request your participation in a future survey. By providing this information, you enable us to create a code to link your response from this survey with responses to a future survey. We respect your privacy, and the responses you provide will only be accessible to the study team.

Birthdate (MM/DD/YYYY)? EX: September 18, 1972 = 09/18/1972. (1)

Initials (first and last name only)? EX: John Doe = JD. If you have multiple first and last names, please provide the first letter of your first name and the first letter of your first last name. EX: Maria Eugenia Alvarez Garcia = MA. (2)

What is your LADWP Customer Access Number (CAN)? We will use this information to verify that the residence under your account is eligible for the SmartPower Partners Program. You can find your 10-digit CAN in the upper left-hand corner of your bill.

How often do you do the following?

	Never (1)	Less than Once a Month (2)	Once a Month (3)	2-3 Times a Month (4)	Once a Week (5)	2-3 Times a Week (6)	Daily (7)
Search for things online/ on the internet (1)	❍	❍	❍	❍	❍	❍	❍
Check email on a computer (2)	❍	❍	❍	❍	❍	❍	❍
Check email on my mobile phone (3)	❍	❍	❍	❍	❍	❍	❍
Check email on my tablet device (e.g., iPad) (4)	❍	❍	❍	❍	❍	❍	❍
Send or receive text messages on my mobile phone (5)	❍	❍	❍	❍	❍	❍	❍
Use Facebook (6)	❍	❍	❍	❍	❍	❍	❍

Use Twitter (7)	❍	❍	❍	❍	❍	❍	❍
Check out videos on YouTube (8)	❍	❍	❍	❍	❍	❍	❍
Read or write Blogs (9)	❍	❍	❍	❍	❍	❍	❍
Use other internet-based service (please specify) (10)	❍	❍	❍	❍	❍	❍	❍

How often do you use the following?

	N/A - I don't have access to this device/service (1)	Never (2)	Less than Once a Month (3)	Once a Month (4)	2-3 Times a Month (5)	Once a Week (6)	2-3 Times a Week (7)	Daily (8)
Internet on computer at my home (1)	❍	❍	❍	❍	❍	❍	❍	❍
Internet on computer at my place of work (2)	❍	❍	❍	❍	❍	❍	❍	❍
Internet browser on public computer (e.g., library) (3)	❍	❍	❍	❍	❍	❍	❍	❍
Internet browser on my smart phone (4)	❍	❍	❍	❍	❍	❍	❍	❍
Internet browser on my tablet device (e.g., iPad) (5)	❍	❍	❍	❍	❍	❍	❍	❍
Basic	❍	❍	❍	❍	❍	❍	❍	❍

cell phone without internet access (6) Mobile phone "apps" (7)	❍	❍	❍	❍	❍	❍	❍	❍

Have you signed up for any of the following programs through LADWP in the past 6 months?

	Yes (1)	No (2)
Green Power Program (1)	❍	❍
Electric Vehicle Program / Electric Vehicle Charger Rebate (2)	❍	❍
Low Income Weatherization Assistance Program (technician from LADWP visited your home to fix air leaks, identify indoor air quality problems, install energy-saving devices, etc) (3)	❍	❍
Low Income Refrigerator Replacement Program (4)	❍	❍
RETIRE Program (5)	❍	❍
Energy Upgrade California (6)	❍	❍
Solar Incentive Program (7)	❍	❍
Time Of Use (TOU) Rate (8)	❍	❍
Other energy efficiency program (please specify) (9)	❍	❍

What is your overall attitude toward LADWP?

- ❍ Very Negative (1)
- ❍ Negative (2)
- ❍ Somewhat Negative (3)
- ❍ Neutral (4)
- ❍ Somewhat Positive (5)
- ❍ Positive (6)
- ❍ Very Positive (7)

How satisfied are you with the current home energy management options provided to you by LADWP?

- ❍ Very Dissatisfied (1)
- ❍ Dissatisfied (2)
- ❍ Somewhat Dissatisfied (3)
- ❍ Neutral (4)
- ❍ Somewhat Satisfied (5)
- ❍ Satisfied (6)
- ❍ Very Satisfied (7)

In the future, LADWP would like to provide all of its customers with a free energy management service that lets you see how much electricity is being used in your home, in almost real time, and gives you tips to help you save energy and money. This free service may be provided using one of several methods, such as a web site, a smart phone "app", or a display that can be installed inside of your home. Which home energy management method appeals most to you (choose one)?

- ❍ A free web site (please indicate your reasoning) (1) _____
- ❍ A free smartphone app (please indicate your reasoning) (2) _____
- ❍ A free in-home display (please indicate your reasoning) (3) _____
- ❍ Other (please specify) (4) _____
- ❍ None of these options would appeal to me (please indicate your reasoning) (5) _____

How would you rate your knowledge of "Smart Meters"?

- ❍ I have never heard about them (1)
- ❍ I don't know much about them (2)
- ❍ I know a little bit about them (3)
- ❍ I know a good deal about them (4)
- ❍ I know a lot about them (5)

In your own words, what is a smart meter? What you like about them? What don't you like about them?

What is your general opinion of Smart Meters?

- ❍ Very negative (1)
- ❍ Negative (2)
- ❍ Somewhat negative (3)
- ❍ Neutral (4)
- ❍ Somewhat positive (5)
- ❍ Positive (6)
- ❍ Very positive (7)
- ❍ I don't know enough about them to give an opinion (8)

"Smart grid" refers to technology being used to bring electricity delivery systems into the 21st century, using computer-based remote control and automation. Two-way communication technology and computer processing that have been used for decades in other industries makes these systems possible. They offer many benefits to utilities and consumers, including improved energy efficiency on the electricity grid and in utility customers' homes and offices (US Department of Energy, 2012).

Please check all that apply.

- ❑ I know someone besides me who has a smart meter. (1)
- ❑ I have spoken to someone who has a smart meter about smart meters and / or smart grid. (2)
- ❑ I have spoken to someone who does not have a smart meter about smart meters and / or smart grid. (3)

Answer If Please check all that apply. I have spoken to someone who has a smart meter about smart meters and / or smart grid. Is Selected Or Please check all that apply. I have spoken to someone who does not have a smart meter about smart meters and / or smart grid. Is Selected

You indicated that you have discussed Smart Meters with others. What were the key points of the conversation? What were other people's opinions of Smart Meters?

Which of the following benefits of investing in a "smart grid" would be most important to you personally?

	Not at all Important (1)	Very Unimportant (2)	Somewhat Unimportant (3)	Somewhat Important (4)	Very Important (5)	Extremely Important (6)
Making our electrical system more efficient (1)	❍	❍	❍	❍	❍	❍
Reducing our dependence on fossil fuels (2)	❍	❍	❍	❍	❍	❍
Improving our aging electric infrastructure (3)	❍	❍	❍	❍	❍	❍
Greater choice in how much I pay for electricity (4)	❍	❍	❍	❍	❍	❍
Greater control over my electric bill (5)	❍	❍	❍	❍	❍	❍
Improving resilience against attack and natural disaster (6)	❍	❍	❍	❍	❍	❍
Fostering economic growth and	❍	❍	❍	❍	❍	❍

creating jobs (7)						
Better integration of renewable sources of electricity (e.g., solar) (8)	❍	❍	❍	❍	❍	❍
Ability to support a growing number of plug-in electric vehicles (9)	❍	❍	❍	❍	❍	❍
More reliable electric power (e.g., fewer blackouts) (10)	❍	❍	❍	❍	❍	❍
Greater choice of when to purchase and use electricity (11)	❍	❍	❍	❍	❍	❍
Reducing greenhouse gas emissions and protecting the environment	❍	❍	❍	❍	❍	❍

(12) Better information about my home energy use (13)	❍	❍	❍	❍	❍	❍

Energy use relates to many broader issues and parts of daily life. Think about the following statements in relation to energy efficiency. Rank the top five statements that are most important to you by dragging and dropping. I am motivated to do my part in terms of energy efficiency because:

_____ It could promote United States energy security / independence (not relying on foreign production) (1)
_____ My family could benefit (2)
_____ It aligns with my religious values (3)
_____ Environmental quality (local and/or global) could benefit (4)
_____ My health and/ or the health of other people could benefit (5)
_____ My economic well-being could improve (6)
_____ The well-being of the economy at large could improve (7)
_____ My friends, family members, or colleagues would like it if I did (8)
_____ My friends, family members, or colleagues engage in energy-efficient behaviors (9)
_____ My quality of life could improve (10)
_____ It is the right thing to do (11)
_____ Other (please specify) (12)

Please indicate the extent to which you agree or disagree with each of the following statements, using the scale provided.

	Strongly Disagree (1)	Disagree (2)	Neither Agree nor Disagree (3)	Agree (4)	Strongly Agree (5)
I tend to know about new ways to save energy before most other people do. (1)	❍	❍	❍	❍	❍
If I heard about a new way to save energy, I would be interested enough to check it out. (2)	❍	❍	❍	❍	❍
I try to buy energy efficient household appliances. (3)	❍	❍	❍	❍	❍
I try to use appliances like my clothes dryer or dishwasher relatively early in the morning or late in the evening for energy efficiency and/or financial reasons. (4)	❍	❍	❍	❍	❍
I tend to start using new technologies/devices before most other people. (5)	❍	❍	❍	❍	❍
People in my social environment (family, friends, coworkers, etc.) make me feel that I should adopt certain	❍	❍	❍	❍	❍

energy-saving behaviors. (6)					
Higher energy bills would put a big dent in my financial resources. (7)	❍	❍	❍	❍	❍
Every citizen must take responsibility for conserving energy. (8)	❍	❍	❍	❍	❍
Energy efficiency is important to me. (9)	❍	❍	❍	❍	❍
Energy conservation is important to me. (10)	❍	❍	❍	❍	❍
I watch my energy use habits to make sure I'm not wasting energy. (11)	❍	❍	❍	❍	❍
I specifically look for energy-efficient versions of appliances and/or products. (12)	❍	❍	❍	❍	❍

Please rate the extent to which you agree or disagree with each of the following statements.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neutral (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
I often feel a strong connection to nature. (1)	❍	❍	❍	❍	❍	❍	❍
I think of nature as a family that I belong to. (2)	❍	❍	❍	❍	❍	❍	❍
I see myself as a part of the greater circle of life. (3)	❍	❍	❍	❍	❍	❍	❍
Humans are more important than plants and animals. (4)	❍	❍	❍	❍	❍	❍	❍
I feel related to animals and plants. (5)	❍	❍	❍	❍	❍	❍	❍
I feel I belong to the Earth and that the Earth belongs to	❍	❍	❍	❍	❍	❍	❍

me. (6)							
I feel that all living things in this world are connected, and I am a part of that. (7)	❍	❍	❍	❍	❍	❍	❍
There is something that every living thing shares. (8)	❍	❍	❍	❍	❍	❍	❍
Like the tree in the first, I feel I belong to nature. (9)	❍	❍	❍	❍	❍	❍	❍
I don't feel part of nature. (10)	❍	❍	❍	❍	❍	❍	❍

Participating in energy efficiency is difficult for me due to...

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
The physical construction of my residence (1)	❍	❍	❍	❍	❍	❍	❍
The up-front costs of energy-efficient investments or repairs (2)	❍	❍	❍	❍	❍	❍	❍
The age of my home (3)	❍	❍	❍	❍	❍	❍	❍
Lack of time (4)	❍	❍	❍	❍	❍	❍	❍
I'm not sure what to do (5)	❍	❍	❍	❍	❍	❍	❍
I don't think I have the required technical experience (6)	❍	❍	❍	❍	❍	❍	❍
I do not know where to get information	❍	❍	❍	❍	❍	❍	❍

(7) My family's medical issues (8)	❍	❍	❍	❍	❍	❍	❍
A lack of cooperation of others in my residence (9)	❍	❍	❍	❍	❍	❍	❍
Other (please specify) (10)	❍	❍	❍	❍	❍	❍	❍

Did the Smart Power Partners program help you learn new things about energy use and energy management?

- ❍ Yes (1)
- ❍ No (2)

Did the Smart Power Partners program help you reduce your energy consumption and/or save money on your electric bill?

- ❍ Yes (1)
- ❍ No (2)

SmartPower Partners initially contacted you every other week. Please rate your level of satisfaction with this frequency of contact.

- ❍ Very Dissatisfied (1)
- ❍ Dissatisfied (2)
- ❍ Somewhat Dissatisfied (3)
- ❍ Neutral (4)
- ❍ Somewhat Satisfied (5)
- ❍ Satisfied (6)
- ❍ Very Satisfied (7)

Overall, how satisfied were you with the energy management tools provided by the Smart Power Partners program?

- ❍ Very Dissatisfied (1)
- ❍ Dissatisfied (2)
- ❍ Somewhat Dissatisfied (3)
- ❍ Neutral (4)
- ❍ Somewhat Satisfied (5)
- ❍ Satisfied (6)
- ❍ Very Satisfied (7)

What did you like about the Smart Power Partners energy management tools?

What could be improved about the Smart Power Partners energy management tools?

Please respond to the following questions about the Smart Power Partners energy management tools.

	Please rate how useful each tool was for you.						Please rate your level of enjoyment for each tool.					
	Very useless (1)	Useless (2)	Neutral (3)	Useful (4)	Very useful (5)	Did not use this tool (6)	Hated (1)	Disliked (2)	Neutral (3)	Liked (4)	Loved (5)	Did not use this tool (6)
Tips (1)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Home audit (2)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Seeing my own home energy use (3)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Comparisons of my home energy use to others (4)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Earning badges and statuses (5)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Setting Goals (6)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Monitorin	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍

g goal progress (7) Save Power Events (8)	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍

How satisfied were you with the Save Power Events?

- ❍ Very Dissatisfied (1)
- ❍ Dissatisfied (2)
- ❍ Somewhat Dissatisfied (3)
- ❍ Neutral (4)
- ❍ Somewhat Satisfied (5)
- ❍ Satisfied (6)
- ❍ Very Satisfied (7)

What did you like about Save Power Events?

What could be improved about Save Power Events?

How satisfied were you with the SmartPower Partners program overall?

- ❍ Very Dissatisfied (1)
- ❍ Dissatisfied (2)
- ❍ Somewhat Dissatisfied (3)
- ❍ Neutral (4)
- ❍ Somewhat Satisfied (5)
- ❍ Satisfied (6)
- ❍ Very Satisfied (7)

ppendix H Smart Grid LA Follow Up Survey Summary Report

Smart Grid LA Follow Up Survey Summary Report

Los Angeles Department of Water and Power Smart Grid Regional Demonstration Program

Customer Behavior Project

July 1, 2016

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1. Change History

c. Author: Ellen Dux
d. Reviewer/Approvers: Justin Powels, Tulia Vazquez Montes

2. Executive Summary

The primary goal of this study is to assess changes in energy behaviors, as well as attitudes and perceptions related to energy use and management technologies, among LADWP customers. These findings serve as follow-up to the initial 2013 baseline study (CB9). Data collected from this June 2016 survey (at conclusion of Operations Phase) is evaluated relative to the data collected during the 2013 Pre-Ops survey. This comparison will provide insights into how customers' thoughts and opinions have evolved based on their exposure to Smart Grid tools, programs, and outreach efforts.

A total of 213 LADWP customers completed the survey via phone interviews. The sample included 113 Smart Grid Regional Demonstration Project (SGRDP) customers and 100 non-SGRDP customers. 7107 calls were placed in total.

In order to ensure accurate sample representation and capture more robust data, an additional 227 LADWP customers completed the same survey online - 161 SGRDP customers and 66 non-SGRDP customers. Results from this sample sub-group, however, are not included in the comparative analysis of trends between the baseline and follow-up surveys.

Finally, 34 SGRDP customers who registered for the Smart Power Partners web portal were surveyed about their experiences using the portal. Though this sample size is too small to be statistically significant, the findings were instructive.

Key Findings:

- Knowledge about Smart Meters is quite limited for both SGRDP and non-SGRDP customers, although overall their opinions are generally positive. This is little changed since the 2013 baseline survey;
- Compared to the 2013 baseline survey, even fewer SGRDP customers are aware that they have a Smart Meter; only 19% correctly identified having one installed at their homes;

- The acceptability of having a Smart Meter installed also has declined in the last three years; only 46% of respondents in 2016 found it acceptable, compared to 63% in 2013;
- In 2016, 63% of SGRDP and non-SGRDP customers are confident about their ability to conserve energy in comparison to other Southern Californians, down from 70% in 2013. Their perceived possible reduction amount declined as well, from 36% in 2013 to 27% in 2016;

- Despite the low acceptance rate for Smart Meters, both SGRDP and non-SGRDP customers recognize some benefits of having one, including reduced electric bills, a more efficient electric grid, and a reduction in disruptive blackouts/brownouts; and
- In 2016, 75% of non-SGRDP customers are likely to believe that energy conservation is very important, compared to 65% of SGRDP customers. Numerous respondents from both sample sub-groups are taking actions to reduce their energy usage, including turning off lights and other appliances when not in use; upgrading to energy efficient appliances; and turning up AC temperature/turning down heater temperature.

3. Demonstration Overview

a. Smart Grid Capabilities and Functions Demonstrated

The study demonstrated the following functions from the SOPO:

- Demonstrate the impact of Smart Grid communication systems and processes on customer usage patterns
- Demonstrate communication and media content on Smart Grid deployment, incorporating changes observed in awareness, attitudes, and energy use behaviors

b. Smart Grid Benefits Demonstrated

<u>Employing Costumer Behavior Strategies to Optimize Demand Response Efforts</u>

Electric utilities allocate considerable resources to avoid power interruptions. In recent years, U.S. utilities are investing upwards of $700 million per year in demand response (DR) strategies to curtail peak load and minimize the need for additional power generation, which is environmentally and economically costly (US Energy Information Administration, 2013).

DR forecasting models predict when, where, and how much energy will be used, but solving the critical problem of *how* to reduce that demand requires programs that encourage utility customers to make voluntary behavioral changes to curtail energy use during peak hours. The U.S. Federal Energy Regulatory Commission characterizes DR as a "bottom-up process…driven by changes in customer behavior." Because voluntary behavior changes can be notoriously difficult to affect and maintain, social science approaches should be leveraged to promote them. And while decades of research support the effectiveness of social science tools in changing user behaviors to reduce energy consumption, additional investigation is required to determine optimal strategies.

For instance, a number of white papers suggest that DR programs that offer monetary incentives can be effective in reducing peak demand. However, incentives for promoting continuous, long-term energy conservation may differ from those that support discrete, time-delimited behavior change. Also, DR tools now can be delivered to customers via new technologies such as mobile apps, web portals, and in-home displays. Thus, understanding which technologies customers are willing to engage with is critical to shaping DR programs that will have positive customer uptake. Finally, persuasive messaging can be an effective strategy for promoting participation in DR events. But understanding what motivators resonate with different customer segments is vital for creating messaging that will ensure successful DR efforts.

c. List of Objectives/Scope

The primary goal of this study is to assess changes in energy behaviors, as well as attitudes and perceptions related to energy use and management technologies, among LADWP customers. These findings serve as follow-up to the initial 2013 baseline study (CB9). Data collected from this June 2016 survey (conclusion of Operations Phase) is compared to data collected from the 2013 Pre-Ops survey to provide insights into how customers' thoughts and opinions evolved over time based on their exposure to Smart Grid programming. Surveying both SGRDP and non-SGRDP customers allows for exploration of differential rates of change among these subgroups.

<u>Hypothesis</u>

Before conducting this study, we hypothesized that attitudes towards Smart Grid energy management technologies and tools and a willingness to employ them would have become more positive over time, as well as becoming more positive among SGRDP customers relative to non-SGRDP customers. Interacting with Smart Grid program elements and engaging with energy data would be hypothesized mediators of these changes.

However, due to project deployment limitations during SGRDP Operations Phase, SGRDP customers were not exposed to any Smart Grid initiatives in the time between the 2013 baseline survey and the 2016 follow up survey, other than having Smart Meters installed in their homes and being given access to an energy management web portal with limited functionality. Due to the nullifying effect of this unexpected but significant delay in project deployment, we hypothesized that SGRPD customers' Smart Grid attitudes would remain about the same in the follow up survey as in the baseline survey, and also would remain more positive than non-SGRDP customers' attitudes. Finally, we hypothesized that the Portal Registrants subgroup would be more engaged and positive about Smart Grid than non-Portal registrants.

d. Mapping to the SOPO & Deliverables

The following deliverables from the SOPO are presented in this report:

13. Identification of the key decision factors in the adoption of Smart Grid related technologies.
14. Identification of the key socio-demographic and community structure variables in the Smart Grid adoption process.
15. Delivery of comprehensive data, analysis, and models relating socio-demographic compositions and customer use types to Smart Grid technology acceptance and use patterns.
16. Final report documenting the results of the demonstration.

4. Descriptions of Methodologies

Participants: Individuals could participate in the study if they were adult LADWP customers. Eligibility was determined by survey responses.

A total of 213 LADWP customers completed the survey via phone interviews. A market research company conducted the interviews by phone using a highly structured interview protocol (see Appendix B for interview questions). The sample included 113 SGRDP customers and 100 non-SGRDP customers. In total, 7107 calls were placed; of these, 2.9% were completed interviews, 13.7% were scheduled call backs, 3.5% declined to participate, and .8% were ineligible to participate. Approximately 4% of calls were conducted in Spanish.

As noted earlier, an additional 227 LADWP customers completed the survey online - 161 SGRDP customers and 66 non-SGRDP customers. Also, 34 SGRDP customers who registered for the Smart Power Partners web portal were surveyed about their experiences using the portal.

Similar to the 2013 baseline survey sample, this follow up survey sample roughly matched demographic characteristics for Los Angeles County based on U.S. Census data, except for ethnic distribution, educational attainment, and homeownership rate. The sample significantly under-represented Latinos and over-represented Asians relative to Los Angeles County demographic characteristics. See Tables 1 and 2 below for details.

Table 1. Demographic characteristics of sample relative to baseline survey and Los Angeles County

	Total Sample		**Smart Grid Customers**		**Non-Smart Grid Customers**		**LA County**
	2013	**2016**	**2013**	**2016**	**2013**	**2016**	
Gender (% female)	**56**	**48**	**54**	**46**	**57**	**51**	**51**
Mean age	**48**	**52**	**49**	**44**	**46**	**59**	
Ethnicity							
African American	15	16	16	15	13	18	13
Asian / Asian American	8	15	8	20	8	9	5
Caucasian	43	38	45	35	42	40	50
Latino	22	17	20	15	25	19	49
Native American / Pacific	2	1	2	1	2	0	0

Islander							
Multiracial	4	6	4	7	4	5	5
Language Spoken at Home							
English	81	79	82	83	80	74	40
Spanish	13	8	11	5	15	11	
Other language	4	13	8	12	6	14	60
Marital Status							
Never married	37	32	32	42	40	20	
Currently married	39	42	40	44	37	39	
Domestic partnership	3	3	1	4	5	2	
No longer married	17	16	20	6	14	27	
Separated	4	4	3	3	4	5	

Table 2. Household characteristics of sample relative to baseline survey and Los Angeles County

	Total Sample	**Smart Grid Customers**	**Non-Smart Grid Customers**	**LA County**

	2013	2016	2013	2016	2013	2016	
Education							Or higher:
Less than high school	7	4	6	3	8	6	
High school/GED	12	11	12	8	13	15	75
Technical or trade school	2	1	2	0	1	1	
Some college or associates degree	25	25	26	20	25	31	
4-year college degree	29	31	28	35	30	25	32
Completed graduate school or professional degree program	25	25	26	32	25	18	
Homeownership							
Own	40	51	41	39	40	65	37
Rent	59	47	58	61	59	32	
Type of Residence							
Single family home	47	52	48	41	46	64	
Multi-family home	35	37	36	50	34	22	
Duplex/Triplex/Quad	8	2	5	2	11	2	
Townhome	6	5	6	6	6	4	
Mobile home	0	1	0	0	0	3	

Other	3	2	4	1	3	4	
In same house as last year							85

Procedures: Trained market researchers conducted structured phone interviews with respondents. Respondents were selected at random from LADWP customer database. Surveys were conducted by RKS, a market research company with whom LADWP had previously worked. The mean duration of calls was 15 minutes.

Materials: Recruitment materials: Interviewers opened with an introductory recruitment statement. The recruitment script is provided in Appendix A.

Structured interview script/survey: If participants were eligible and agreed to participate, interviewers proceeded with survey questions, which included household characteristics, demographic characteristics, technology adoption, smart meters and related technology, and energy efficiency (see Appendix B for survey).

5. Summary of Major Findings and Conclusions

Beliefs related to Smart Meters: In 2016, only 19% of SGRDP customers correctly reported having a Smart Meter installed. Respondents also indicated their level of knowledge and opinions about Smart Meters, and to what extent they would accept having a Smart Meter installed at their home. As in 2013, over one-third of all respondents had never heard of Smart Meters at all; in general the sample reported very low levels of knowledge about them. Interestingly, despite not knowing much about Smart Meters, respondents generally held neutral or favorable opinions towards them, and most indicated it would be acceptable if LADWP were to install one at their homes (this percentage declined from 2013 to 2016, however). See Figures 3, 4 and 5 below.

Figure 3. Self-reported knowledge of Smart Meters

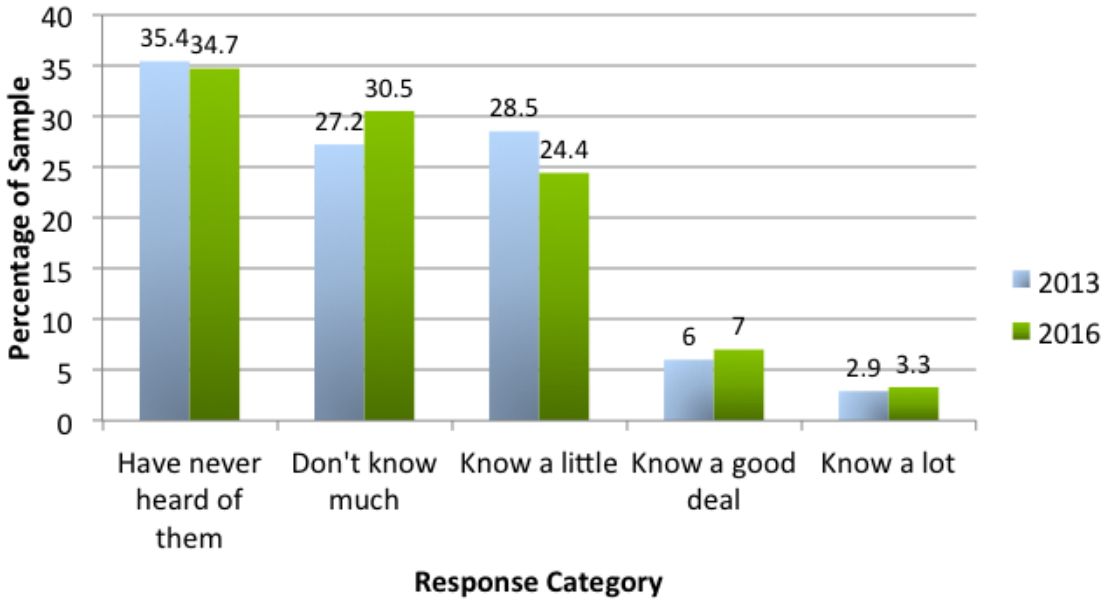


Figure 4. Opinions about Smart Meters

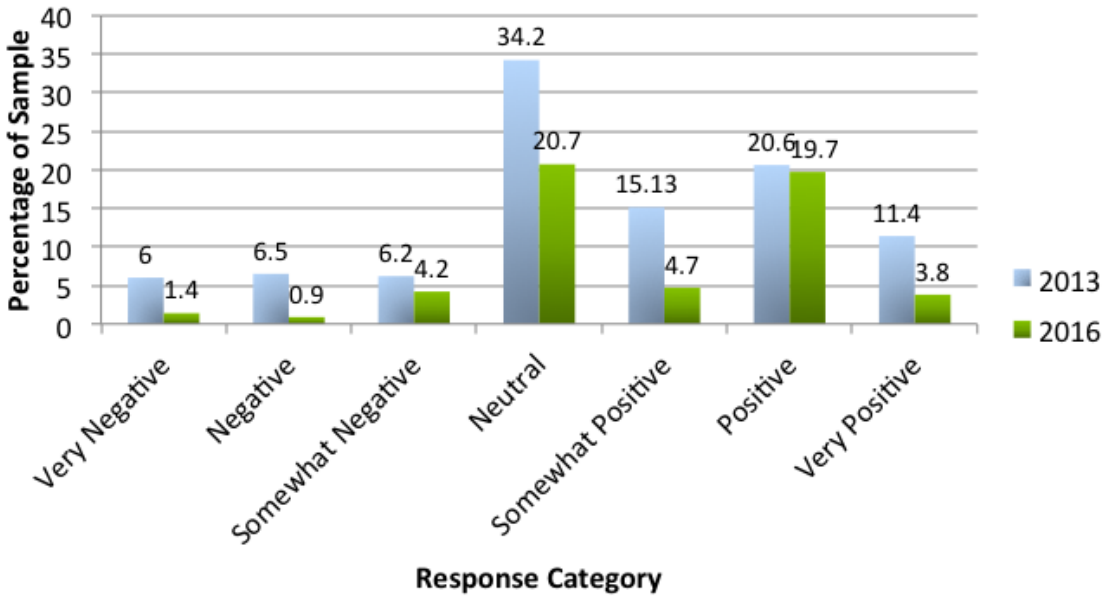
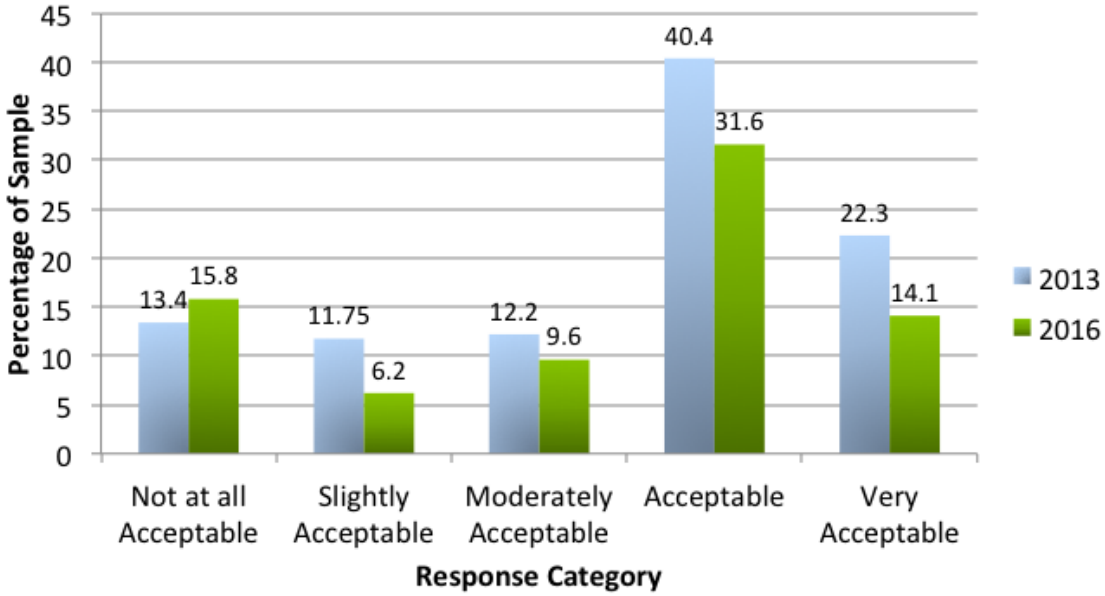


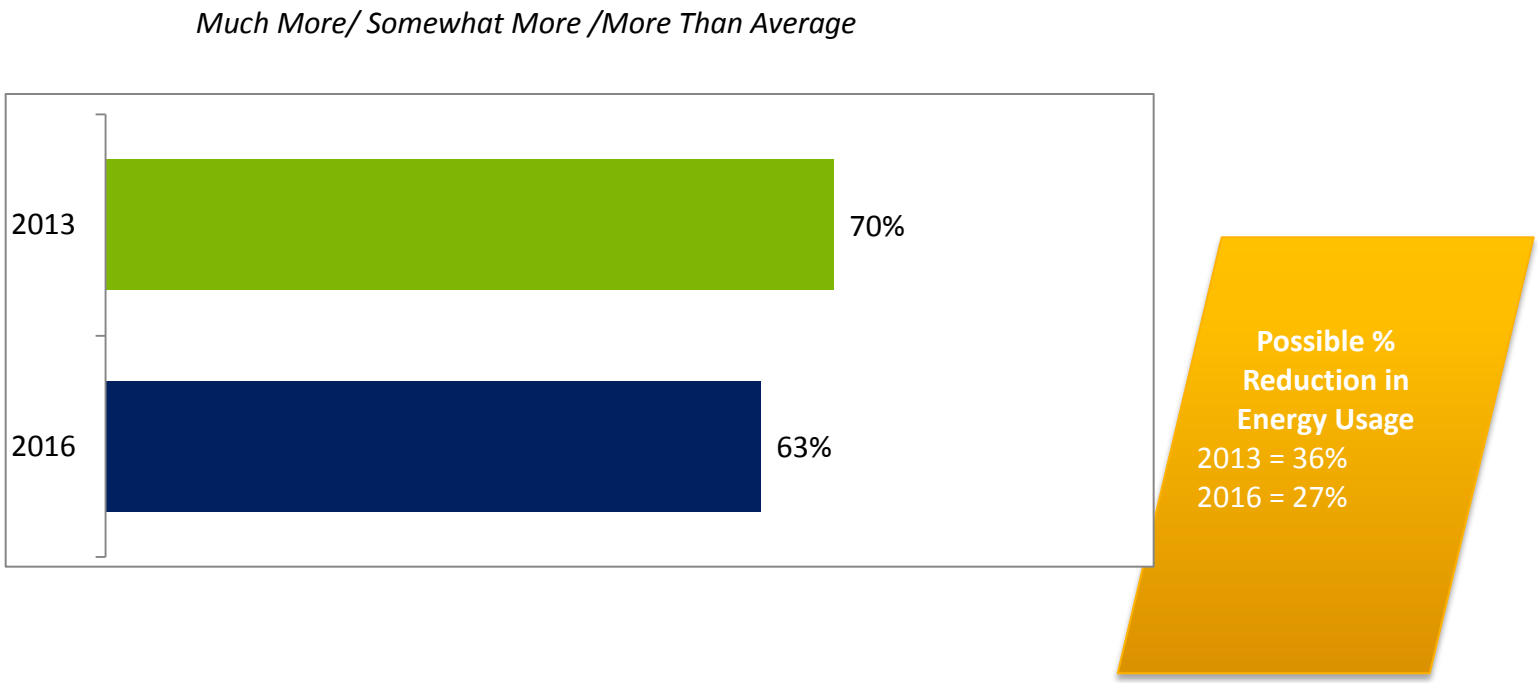
Figure 5. Acceptability of installing a Smart Meter



Normative Influences: Normative influence refers to the influence of other people on one's own decisions and preferences. To better understand how normative influences could be leveraged to promote Smart Grid adoption, questions related to normative influences on energy use were asked. Emphasizing descriptive norms that highlight the conservation efforts of others have been shown in other experiments to promote conservation among target customers.

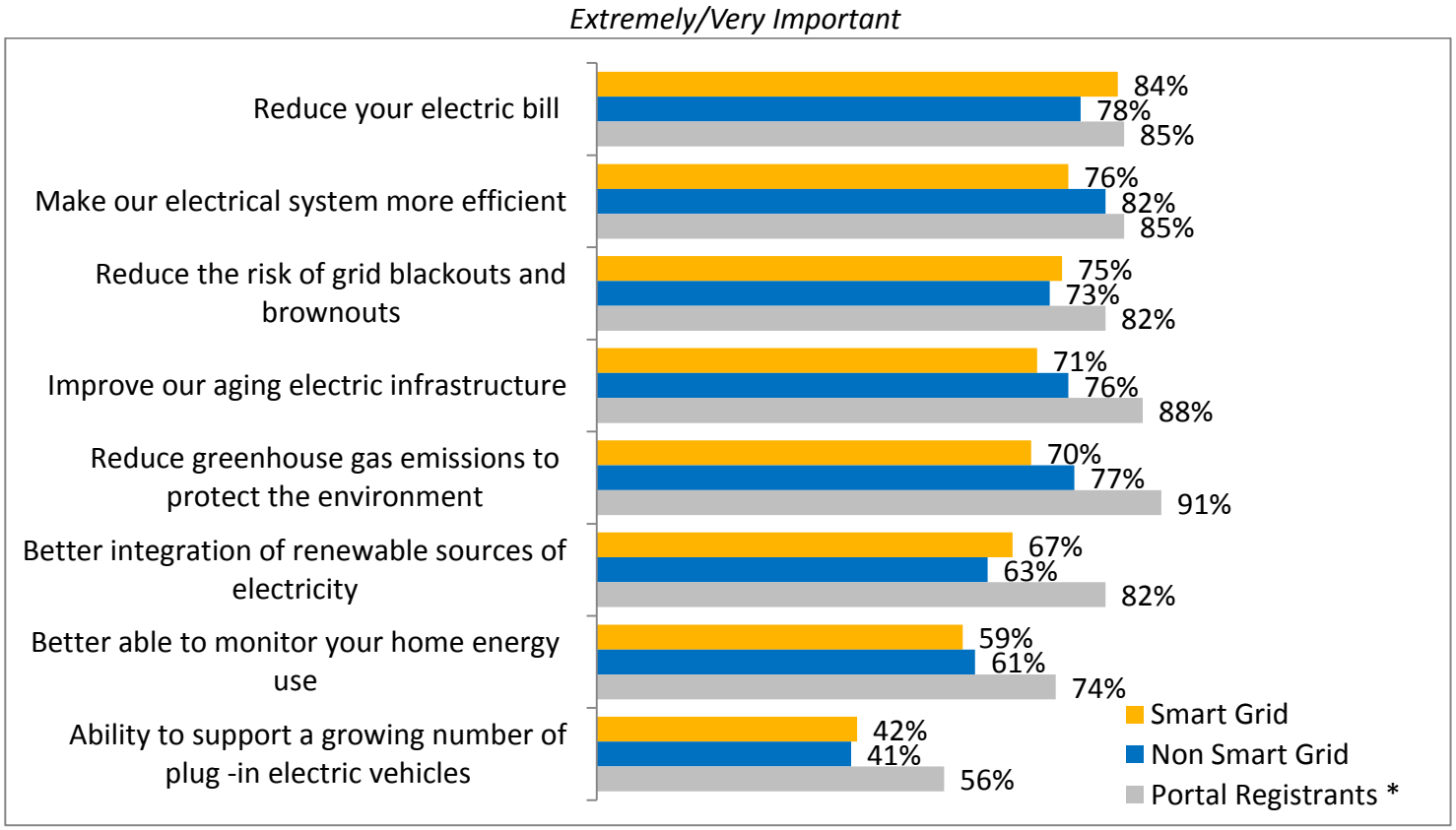
Respondents were asked to estimate the extent to which they conserve energy, compared to other Southern Californians. In 2016, almost two thirds of the sample (63%) believed their household was conserving energy at least somewhat more than average, in comparison to their neighbors. However, "much more/somewhat more/more than average" responses dropped from 70% in 2013. The tendency for people to believe they are performing better than average is a common cognitive bias. Respondents also believed they could achieve very high reductions in energy if their household made a special effort to conserve, although that estimated amount also declined from 36% in 2013 to 27% in 2016.

Figure 6. Respondents' beliefs about Southern Californians' conservation efforts



Motivators for Engaging with Smart Grid: In order to identify potential motivators for Smart Grid engagement that can be incorporated into customer messaging and outreach strategies, respondents were queried about perceived Smart Grid benefits. The highest-ranking motivators – ranked as extremely or very important - were reducing electric bills; making the electric system more efficient, and minimizing the likelihood of black/brownouts.

Figure 7. Motivators for Smart Grid engagement



Home Energy Management Technologies: Respondents reported on a number of issues related to home energy management technologies and interfaces. None of the mean ratings differed based on SGRDP participant status. Overall, customers' satisfaction with the energy management options offered by LADWP is neutral to satisfied (consistent with 2013), but there is declining interest in participating in any of these options including TOU pricing plan, free in-home display, or free web portal. Overall, the most frequently endorsed option was the free in-home display, with almost 40% of respondents indicating they were likely or very likely to use it. See Figures 8, 9, 10 and 11.

*Web Portal Registrants***:** 3% of all SGRDP customers who were offered access to the free Smart Power Partners web portal registered for it. Although small, this customer sub-group is likely to be highly engaged in their energy usage and sustainability-related issues, and early adopters of energy management techniques and technologies.

Figure 8. Satisfaction with current home energy management options

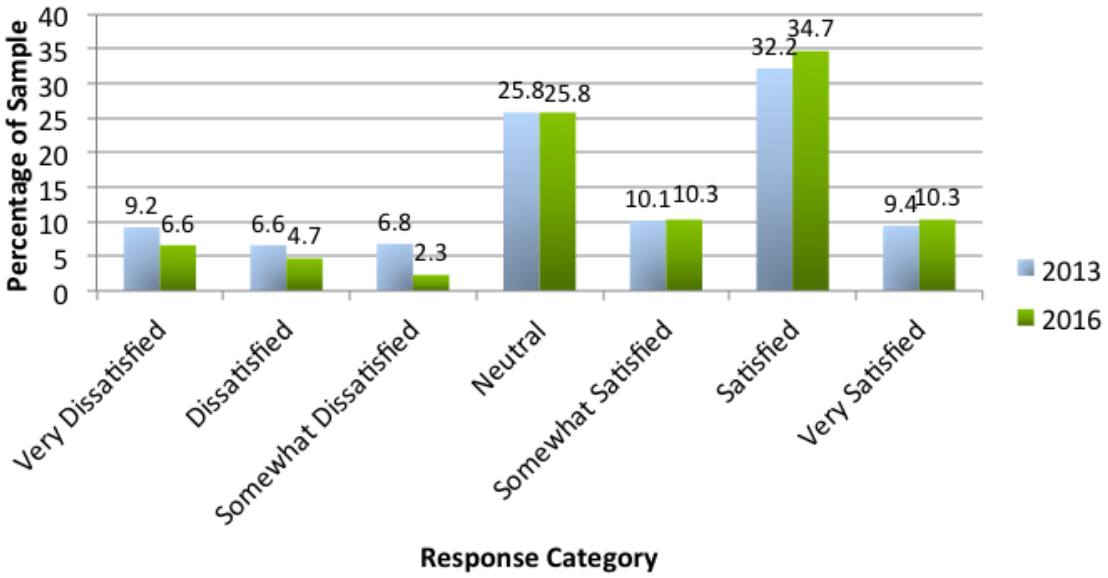


Figure 9. Likelihood of signing up for TOU pricing plan

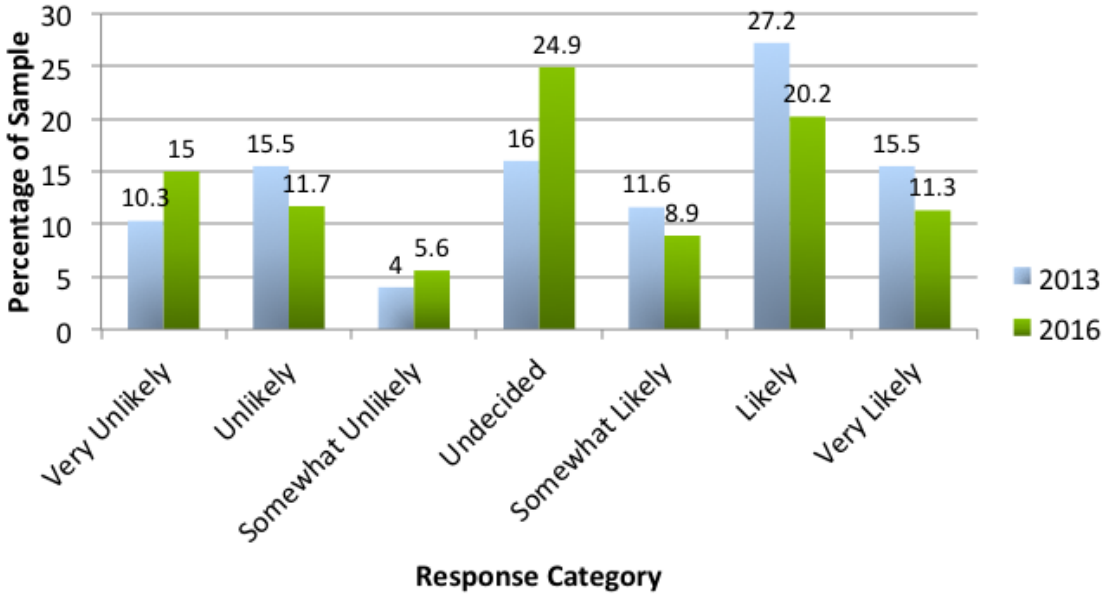

Percentage of Sample
30
25
20
15
10
5
0
10.3
15
15.5
11.7
4
5.6
16
24.9
11.6
8.9
27.2
20.2
15.5
11.3
Very Unlikely
Unlikely
Somewhat Unlikely
Undecided
Somewhat Likely
Likely
Very Likely
Response Category
2013
2016

Figure 10. Likelihood of monitoring home energy use with free in-home display

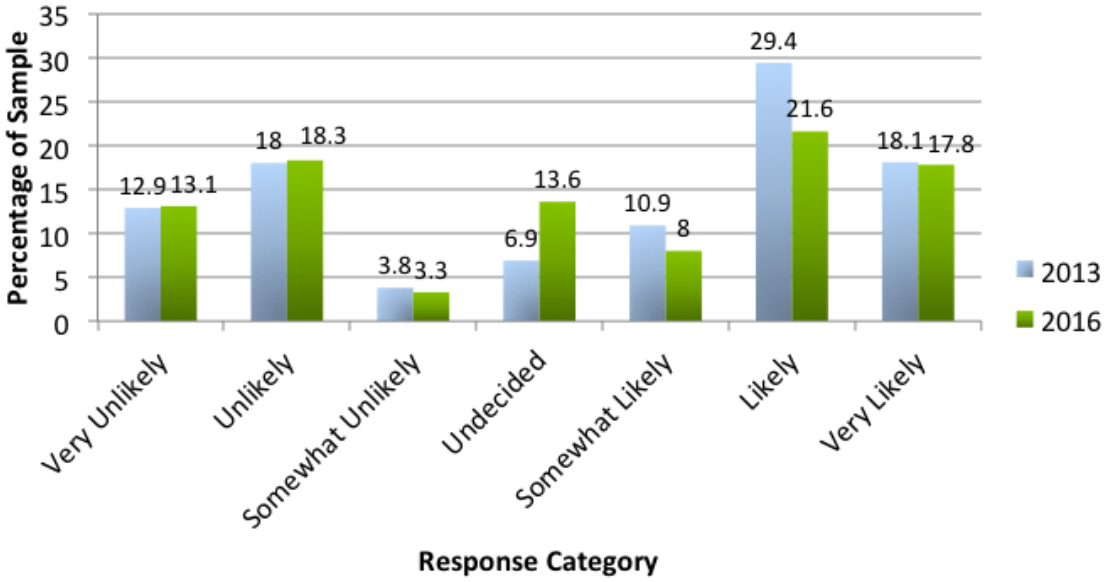
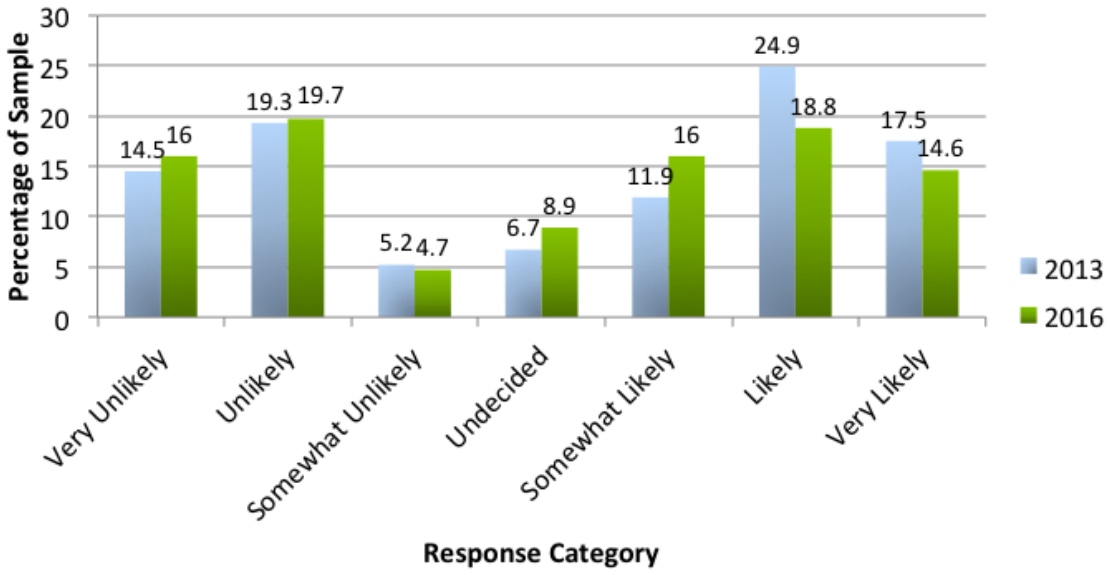


Figure 11. Likelihood of monitoring home energy use with free web portal



Take-Away and Recommendations

- Compared to the 2013 baseline survey, even fewer SGRDP customers who have Smart Meters are aware of it; only 19% correctly identified having one installed at their home. This suggests that the multiple direct mail campaigns and emailed materials regarding meter installation (and eventually, the web portal launch) were either disregarded or were not impactful. More efficient outreach methods should be explored;
- Given low customer knowledge and declining acceptability of Smart Meters, it is critical to provide clear information on their benefits, including dispelling health and data security concerns, and reiterating benefits such as reduction in electric bills and increased grid efficiency;

- In 2016, both SGRDP and non-SGRDP customers are less confident in their ability to conserve energy in comparison to other Southern Californians (63%), vs. 2013 (70%). This suggests an opportunity to utilize key influencers to convey positive social norms about the energy conservation efforts of others that can motivate participants to conserve in their own homes.
- Customers' perceived possible reduction amount declined as well, from 36% in 2013 to 27% in 2016. If participants set conservation goals that cannot be achieved, they may become discouraged and stop trying. This finding suggests that energy consumption awareness should be improved so customers are able to set realistic, achievable conservation goals;
- Based on perceived benefits of Smart Grid, the following benefits should be highlighted in customer outreach and messaging: ability to control electrical bill, efficiency of grid system, and environmental benefits. Additionally, perceived Smart Grid benefits held specifically by Portal Registrants (highly motivated sub-group) should be tested for messaging to the broader customer base as well. These include reduction in greenhouse gasses and support for grid integration of renewable energy.

Limitations

The findings reported here must be considered in light of several limitations. Relative to the population of Los Angeles County, the sample under-represented Latinos and was over-educated. This may limit the generalizability of the findings. A potentially related limitation was the low response rate to the survey invitation calls, which may have resulted in sample bias whereby individuals who tended to have relatively higher levels of educational attainment and identified with non-Latino races agreed to participate. Response bias is a limitation common to all voluntary research studies that limits the generalizability of findings. Finally, self-report data was the only data source for both the 2013 baseline and 2016 follow up surveys.

Strengths

Although the sample did not approximate racial and educational attainment of Los Angeles County population, it was roughly equivalent on all other available measures. Additionally, the structured interview format helped to obtain reliable and valid survey responses.

6. Summary of Next Steps

None, demonstration ended.

7. Appendix: Supporting Documentation

A. Telephone script/recruitment message

CB10 Smart Grid Follow Up Survey

PHONE INTRODUCTION

Hello, my name is _____. I am calling from RKS Research on behalf of the LOS ANGELES DEPARTMENT OF WATER AND POWER. We are not selling anything. LADWP relies on the opinions of customers like you to help determine where and how they should focus their efforts. Our survey today is about new technologies for saving energy and usually takes about 15 minutes. The information that you provide us will be kept confidential.

EMAIL INVITE

LADWP Wants YOUR Opinion!

In an effort to evaluate our customers' needs, and improve our processes to better serve you, LADWP is conducting a survey about new technologies and programs for saving energy. As a valued customer, we invite you to take this brief online survey and share your opinions on this matter.

LADWP has contracted RKS Research & Consulting, an independent marketing research company, to administer the anonymous and confidential survey. We know your time is valuable, so please note the survey will take no more than 15 minutes to complete. If you are willing to participate, please complete the survey by June 7, 2016.

Input from our customers is essential in determining how LADWP can improve in order to provide the services our customers deserve. We are grateful for your time and consideration.

Please take a few minutes to complete the online survey now!

EMAIL INTRODUCTION

Thanks for participating! Today's survey is about new technologies and programs for saving energy.

Appendix B: Survey / Structured Interview Script

SCREENING QUESTIONS

S1. To be sure you're eligible to participate, can you please tell me whether or not you are over the age of 18?

1=YES. Thank you. We ask this question because we are only able to interview legal adults. In what year were you born? _____
(9999=REFUSED)

0=NO. I'm sorry, but we can only interview legal adults. Is there an adult over the age of 18 available right now?
- 1=YES. Can I speak with that person please?
  - 1=YES. Great, I'll hold.
  - 0=NO. Ok, thank you for your time. [end interview]
- 0=NO. I'm sorry, but I must end this interview. Thank you for your willingness to participate

My first few questions refer to your residence. If you have multiple residences, please respond only for your primary residence at which LADWP is your electricity provider. This information will remain confidential and will not be shared with anyone outside of the project team.

S2. What is the address of your primary place of residence?
- Street address (e.g., 123 Main St. Apt 3): _____
- City: _____
- ZIP: _____

S3. How long have you lived at this address?
(99=REFUSED)

_____ years

S4. Do you own or rent this residence?

1=Own
2=Rent
8=Other (please specify) _____
9=(REFUSED)

S5. Including you, how many people live in your household? _____ (99=REFUSED)

S5a. And how many of these are children under age 18?_____ (99=REFUSED)

S5b. And how many of these are adults?_____ (99=REFUSED)

S6. How would you describe your residence? Is it a . . . (READ)

1=Single family home (detached or free-standing residence)
2=Multi-family home (apartment, condo)
3=Duplex, triplex, or 4-plex
4=Townhouse
5=Mobile home
8=Other (please specify) _____
9=(REFUSED)

S7. Who in your household is responsible for paying your electric bill?
(SELECT ALL THAT APPLY) (READ LIST AS NECESSARY)

1=Yourself
2=Spouse or partner
3=Roommate
4=Parent or grandparent
5=Child or grandchild
6=Landlord or building management
7=Boss
88=Other (please specify) _____
9=(REFUSED)

S8. What is your annual household income? Is it . . . (READ)

1=Under $25,000

2=$25,000 - $50,000
3=$50,001-$75,000
4=$75,001-$100,000
5=More than $100,000
9=(PREFER NOT TO ANSWER)

PART 1

Next, I'm going to ask you about your use of various technologies.

T 102. How satisfied are you with the current home energy management options provided to you by LADWP? Would you say you are . . . (READ)
7=Very Satisfied
6=Satisfied
5=Somewhat Satisfied
4=Neutral
3=Somewhat Dissatisfied
2=Dissatisfied
1=Very Dissatisfied
9=(REFUSED)

T 103. For each of the following, please tell me if you are Very likely to do this activity, Likely, Somewhat likely, Undecided, Somewhat unlikely, Unlikely, or Very unlikely to do this activity. First, how likely are you to . . .
7=Very likely
6=Likely
5=Somewhat likely
4=Undecided
3=Somewhat unlikely
2=Unlikely
1=Very unlikely
9=(REFUSED)

a. Use a free website to manage your home energy use
b. Use a free smart phone app to manage your home energy use
c. Use a free in-home display to manage your home energy use
d. Switch to a time of use rate plan (higher rate during daytime hours, lower rate at night)

SMART METERS

The next few questions are about “Smart Meters.” By Smart Meter, I am referring to electric meters which record how much electricity is being used at your home.

T 201. How would you rate your knowledge of Smart Meters? Would you say . . . (READ)
1=You have never heard about them
2=You don't know much about them
3=You know a little bit about them
4=You know a good deal about them
5=You know a lot about them
9=(REFUSED)

T 202. What is your general opinion of Smart Meters? Would you say it is . . . (READ)
1=Very negative
2=Negative
3=Somewhat negative
4=Neutral
5=Somewhat positive
6=Positive
7=Very positive
8=I don't know enough about them to give an opinion
9=(REFUSED)

T 203. Do you currently have a Smart Meter?
1=Yes
2=No
8=Don’t know
9=(REFUSED)

(if response to Q203 was “No” or “Don’t Know”)
T 204. How acceptable would it be if LADWP planned to replace your current electric meter with a Smart Meter? Would it be . . . (READ)
5=Very Acceptable
4=Acceptable
3=Moderately Acceptable
2=Slightly Acceptable
1=Not At All Acceptable
9=(REFUSED)

SAVE POWER (DR) PROGRAM AND SMART GRID

At some point in the future, LADWP will be starting a voluntary "Save Power" program. Under this program, Save Power Events will occur an estimated 5-10 days per year and will last a few hours each. The goal will be to reduce power usage during that time period. You can participate in one event or in all of them, whatever you chose. Prior to such events, LADWP will notify customers to inform them that a Save Power Event is going to occur. During Events, customers who choose to participate will do energy saving actions that are not too uncomfortable or inconvenient (e.g., turn down air conditioning a couple of degrees).

T 301. How likely are you to participate in a Save Power Event? Would you say you are . . . (READ)

7=Very likely
6=Likely
5=Somewhat likely
4=Undecided
3=Somewhat unlikely
2=Unlikely
1=Very unlikely
9=(REFUSED)

T 302 Compared to the average Southern California resident, to what extent do you try to conserve electricity at home? Would you say you try to conserve electricity at home . . .

7=Much More Than Average
6=More Than Average
5=Somewhat More Than Average
4=About The Average
3=Somewhat Less Than Average
2=Less Than Average
1=Much Less Than Average
9=(REFUSED)

T 303. If you and the other people you live with made a special effort to conserve energy, what is the maximum amount of energy reduction you think could be achieved? (0-100%)

____ (0-100%, 999=REFUSED)

304. Smart Grid" refers to technology being used to bring electricity delivery systems into the 21st century, using computer-based remote control and automation. Two-way communication technology and computer processing that have been used for decades in other industries makes these systems possible. They offer many benefits to utilities and their customers, including improved grid energy efficiency.

Which of the following benefits of investing in a "Smart Grid" would be most important to you? For each, please tell me if this would be Extremely important, Very important, Somewhat important, Somewhat unimportant, Very unimportant, or Not at all important. First . . .

6=Extremely important
5=Very important
4=Somewhat important
3=Somewhat unimportant
2=Very unimportant
1=Not at all important
9=(REFUSED)

a. Make our electrical system more efficient
b. Improve our aging electric infrastructure
c. Better integration of renewable sources of electricity (e.g., solar)
d. Ability to support a growing number of plug-in electric vehicles
e. Reduce the risk of grid blackouts and brownouts
f. Reduce greenhouse gas emissions to protect the environment
g. Better able to monitor your home energy use
h. Reduce your electric bill

Part 2: Concept Questions

401. A few more questions about Smart Meters, which are two-way communication digital meters that automatically record how much electricity is being used at your home. Listed below are some possible benefits of having a Smart Meter. For each item on the list, please indicate how much you agree that it would be a benefit (select one for each item).

	Strongly Agree (5)	**(4)**	**(3)**	**(2)**	**Strongly Disagree (1)**
No need for an LADWP meter reader to come to my home to read the meter					

Help you monitor household energy use in real time

Help you reduce household electric bill

Help make LA's electrical grid more efficient

Help reduce the risk of grid blackouts and brownouts

Support grid integration of renewable sources of electricity (e.g., solar)

Support the grid's ability to support more plug-in electric vehicles

Reduce greenhouse gas emissions to help protect the environment

Reduce greenhouse gas emissions to help combat climate change

If response to Q204 was "Slightly or Not at all acceptable" ask Q402)
402. Earlier in the survey you said you prefer not to have a Smart Meter installed at your home. What, if anything, would make it more acceptable for LADWP to install one?

The next few questions are about your personal opinions and experiences regarding water and energy conservation.

403. How important is it to you to conserve energy at home?
- 5=Very important
- 4=Somewhat important
- 3=Somewhat unimportant
- 2=Very unimportant
- 1=Not at all important
- 9=(REFUSED)

(if response to QS5 is greater than 1, ask Q404)
404. In your household, who is most likely to try to conserve energy?
- 1=You
- 2=Other Adults
- 3=Children < 18
- 88=Other
- 9=(REFUSED)

405. What efforts are being made in your household to reduce energy, if anything? < insert if phone (PROBE) What else?>

406. Are you aware of the on-going drought in Los Angeles?

1=Yes
2=No
8=Don't know
9=(REFUSED)

407. Has your household taken any steps to conserve water usage in the past 12 months?
1=Yes
2=No
8=Don't know

(if response to Q407 is yes, ask 408)
408. Have you taken part in any water conservation programs offered through LADWP, such as those that provide a rebate or other incentive to reduce your water use?
1=Yes
2=No
8=Don't know

Part 3: Portal Registrant Questions

(ask question 501- 504 if sample is a portal registrant, otherwise skip)

The next few questions are about the LADWP Smart Power Partners website (www.ladwp.cpm/sgla) that can help customers reduce their energy usage. You may have registered for this website because you have a Smart Meter.

501. Have you visited the Smart Power Partners website?
- 1=Yes
- 2=No
- 8=Don't know

(if response to Q501 is yes, ask 502, 503, and 504)

502. Next I will read a list of items. How would you rate the Smart Power Partners website on a scale where 10 is excellent and 0 is poor?
- a. How well the layout helps you find what you need
- b. The number of steps needed to get where you need to go
- c. The ease of understanding the information provided
- d. How clearly the information is presented
- e. The visual appeal of the site
- f. The balance of text and graphics on the site
- g. The ease of accessing the site from a desktop
- h. The ease of access the site from a mobile device

503. How useful is the Smart Power Partners website in helping you manage your household energy use?
- 4=Very useful
- 3=Somewhat useful
- 2=A little useful
- 1=Not at all useful
- 9=(REFUSED)

504. What other tools could the website include to help you manage your household energy use?

UTILITY VALUE AND SATISFACTION

V1. Overall, how satisfied are you with LADWP? (Select one)

Very Dissatisfied										Very Satisfied	
0	1	2	3	4	5	6	7	8	9	10	Not Sure
○	○	○	○	○	○	○	○	○	○	○	○

V2. If value means that what you receive is worth the price you pay on your bill, how would you rate the overall value of LADWP? (Select one)

Poor										Excellent	
0	1	2	3	4	5	6	7	8	9	10	Not Sure
○	○	○	○	○	○	○	○	○	○	○	○

V3. How would you rate your level of trust in LADWP? (Select one)

No trust at all										Trust completely	
0	1	2	3	4	5	6	7	8	9	10	Not Sure
○	○	○	○	○	○	○	○	○	○	○	○

V4. How much you agree that each of the following describes LADWP. (Select one for each item)

ROTATE LIST	Strongly Disagree				Strongly Agree
Is easy to do business with					
Has the customer's best interest at heart					
Listens to the wants and needs of the local LA community					
Is working hard to provide payment options that meet the needs of customers like you					
Is constantly looking for ways to bring convenience to your lifestyle					

DEMOGRAPHICS

This survey is almost done. We just have a few more questions for classification of different groups of people. The following questions are asked for research purposes only and will be kept confidential.

D1. RECORD GENDER BY OBSERVATION
- 1=Male
- 2=Female

D2. What is the primary language you speak at home?
- 1=Armenian
- 2=Cantonese
- 3=English
- 4=Hindi
- 5=Japanese
- 6=Korean
- 7=Mandarin
- 8=Spanish
- 9=Russian
- 10=Tagalog
- 11=Vietnamese
- 88=Other (please specify) _____
- 99=(REFUSED)

D3. With which ethnic category do you most strongly identify?
- 1=African or African American
- 2=Asian or Asian American
- 3=Caucasian/white
- 4=Latino/a
- 5=Native American or Pacific Islander
- 6=Multiracial
- 88=Other (please specify) _____
- 99=(REFUSED)

D4. What is your marital status?
- 1=Never married
- 2=Currently married
- 3=Currently in a domestic partnership
- 4=No longer married

5=Separated
9=(PREFER NOT TO ANSWER)

D5. What is the highest level of schooling that you have completed?
1=Less than high school
2=High school / GED
3=Technical or trade school
4=Some college or Associate's degree
5=4-year college graduate
6=Completed graduate school or professional degree program
9=(REFUSED)

D6. Do you have any other comments to share?



Thank you for your participation. We appreciate your time. Have a great day.

Interviewer, please add the following information provided to you by LADWP to each respondent’s record:
Customer Name
Customer Address
Customer phone number

Appendix I Electric Vehicle Adoption Baseline Survey

Summary Report

Los Angeles Department of Water and Power Smart Grid Regional Demonstration Program Customer Behavior Project

Electric Vehicle Adoption Baseline Survey

March 31, 2015

This material is based upon work supported by the Department of Energy under Award Number DE-OE0000192 and funding from the Los Angeles Department of Water and Power.

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1. Change History

Author(s): Ellen Dux, Nicole Sintov, Michael Orosz

Reviewer/Approvers: Justin Powels

2. Executive Summary

The transportation sector is one of the largest and fastest growing contributors to greenhouse gas (GHG) emissions associated with climate change. Non-commercial light duty vehicles (LDVs) are responsible for 70% of the road transport sector's carbon emissions. Innovations in LDV technology, such as plug-in hybrid vehicles (PHEV) and battery electric vehicles (EVs), pose great potential for reducing these emissions. However, globally, less than 1% of LDVs are EVs.

Although EV adoption rates are growing, as a new technology, EVs must overcome financial, technical, and social barriers to gain consumer acceptance. The availability of financial incentives is positively correlated with EV adoption rates, but price signals represent only one predictor of EV adoption. Research suggests that social influence also plays an important role in the adoption of new technologies. Recent research has demonstrated the success of persuasion efforts using normative social influence in promoting engagement in a wide variety of green behaviors. Most of these studies have focused on low-cost, habitual behaviors (e.g., recycling). However, other "green" measures require minimal ongoing effort from consumers, but involve high up-front costs (e.g., EVs, solar panels) and offer long-term energy conservation potential. Can social influence also be used as a tool of persuasion in contexts such as these?

The Smart Grid Regional Demonstration Program (SGRDP) Electric Vehicle Adoption Study tested this idea. Below, we present data from a sample of 483 Los Angeles Department of Water and Power (LADWP) residential customers, each of whom responded to a postal mail survey accompanied by one of two versions of a persuasive cover message (emphasizing either social norms or financial benefits associated with EVs). We investigate the impacts of these different persuasion strategies on several measures of EV acceptance and adoption. We also examine income as a moderator of the relationship between persuasive message type and EV adoption.

Overall, we found that respondents had relatively favorable attitudes of EVs. This was marginally higher among the social group relative to the financial group. Individuals were willing to pay slightly more than

$2000 extra for an EV relative to a gasoline vehicle, and when examining by study group, we found that respondents who received the financial message were willing to pay substantially more than were those who received the social message.

Relative to gasoline cars, the sample estimated EV maintenance costs to be about equivalent, fuel costs to be lower, and the purchase price to be higher. These responses did not differ substantially across message group. Additional analyses revealed that response across groups differed as a function of income.

Regarding beliefs about EV ownership, the sample believed that driving an EV indicated they were socially responsible, doing the right thing, and to a lesser extent, acting as a trendsetter for environmentally friendly technologies. Most respondents also believed that EVs were cutting edge, that they lessened environmental impact, and that driving an EV demonstrated concern for the environment. These responses did not differ substantially across message group.

In conclusion, understanding the impacts of different persuasive messaging technique on high-cost green purchase decisions will enable the development of more streamlined and targeted interventions. Such knowledge can then be used to shape strategies for future customer communications at the utility level.

3. An Overview of the Demonstration

At a high level, one goal of the LADWP Smart Grid Regional Demonstration Program is to collect and provide the optimal amount of information necessary for customers to change their behavior in a way that reduces system demands and costs, increases energy efficiency, optimizes the allocation and match of demand and resources, and increases grid reliability.

For the Customer Behavior (CB) project portion of SGRDP, a comprehensive portfolio of customer behavioral studies are being conducted to demonstrate the impact of the adoption of new green behaviors and technologies on customers' energy usage patterns, including electric vehicles.

The transportation sector is one of the largest and fastest growing contributors to greenhouse gas (GHG) emissions associated with climate change. Non-commercial light duty vehicles (LDVs) are responsible for 70% of the road transport sector's carbon emissions. Innovations in LDV technology, such as plug-in hybrid vehicles (PHEV) and battery electric vehicles (EVs), pose great potential for reducing these emissions. However, globally, less than 1% of LDVs are EVs. In the United States, EVs are projected to account for approximately 10% of all LDV sales by 2020, or 1.67 million vehicles.

Although California's transportation sector contributes more than 40% of statewide greenhouse gas emissions, the state also leads the nation in EV sales, with about 40% of the market. Since 2010, more than 102,000 PHEVs have been sold in California; the state governor has set a goal of 1.5 million EVs sold in California by 2025. The Los Angeles area has 80,000 registered PHEVs now; by 2016, EVs will account for approximately 10% of automobiles purchased in the city.

For EVs to plug into the smart grid as a viable distributed storage technology, using behavioral science to increase consumer adoption of EVs, as well as enrollment and optimal participation in charge-discharge programs, are critical. As an emerging technology, EVs face financial, technical, and social barriers to broader consumer acceptance. Perceived costs, including financial and convenience, are cited as top barriers to adoption (Bockarjova & Steg, 2014). The use of financial incentives, such as government subsidies and tax breaks, has been found to be helpful for increasing EV adoption, but price signals represent only one predictor of EV adoption (Bockarjova & Steg, 2014; Sierzchula et al., 2014). Even among consumers with positive attitudes towards EVs, reduced range and long charging times are commonly cited concerns (Ewing & Sarigöllü, 2000; Hidrue et al., 2011). However, the same consumers are willing to pay high, up-front costs for vehicles with longer ranges and faster charging capabilities (Hidrue et al., 2011), highlighting that financial incentives alone are not sufficient to increase adoption rates. Symbolic attributes, which signal the impact of a belonging on one's identity and social status,

have also been identified as a key factor underlying EV purchase (Heffner et al., 2007; Noppers et al., 2014). Communications strategies that tap into these identity concerns may boost adoption rates.

In coming years, as EV adoption rates increase, the load on the electric grid associated with battery charging will increase. Understanding and predicting trends in EV usage patterns and adoption rates in Los Angeles is critical to efficiently managing this impact. This demonstration elucidates customers' current attitudes towards EVs, willingness to adopt EVs, and the impact of normative social influence on EV acceptance and adoption.

a. Smart Grid capabilities and functions demonstrated

The study demonstrated the following functions from the SGRDP's Statement Of Program Objectives (SOPO):

Demonstrate differences and similarities in attitudes, values, and beliefs among distinct target audiences that predict intent to purchase electric vehicles, compared to traditionally powered alternatives;

Demonstrate effective messaging strategies to educate different/distinct target customer types/groups about factors which predict purchase and usage of electric vehicles instead of traditionally powered vehicles.

b. Smart Grid impacts and benefits demonstrated

Planned impacts and benefits from this demonstration include the following:

Understand current LADWP customers' perceptions of and attitudes towards EVs

Provide insights into the role of different persuasive messaging techniques, including financial and normative social influence

Use information to inform utility communications strategies (e.g., charger rebate program)

c. List of objectives/scope

Objectives of the Electric Vehicle Adoption Study include:

- Assess perceptions of and attitudes towards EVs among a random set of LADWP residential customers

- Measure and track baseline attitudes and behaviors relevant to electric vehicles and the potential to buy EVs in the future.

- Identify of key decision factors in the adoption of Smart Grid related technologies

- Integrate behavioral and social factors into the design and implementation of Smart Grid adoption strategies

d. Mapping to the SOPO and deliverables (3.5.3.2)

The following deliverables from the SOPO are presented in this report:

1. Customer communication materials that increase awareness and understanding of benefits of electric vehicles

2. Public outreach and educational forums

3. Trend reports as electric vehicles become more available and widespread, how do drivers (and potential drivers') attitudes, beliefs, and intentions change/adapt/evolve

4. Periodic reports documenting the results of the demonstration

4. Descriptions of the methodologies utilized

Method: Participants

Individuals were eligible to participate in the study if they were current LADWP customers over the age of 18. Eligibility was determined by LADWP customer records (customer status) and survey responses (age). Involvement in the study was voluntary and customers' relationships with LADWP were not affected whether or not they participated. There was no monetary compensation or other incentives for participation.

Age ranged from 20-95, and the mean age of the sample was 54 (SD=16.8). The sample included a higher proportion of Caucasian respondents relative to the County of Los Angeles' racial makeup. The sample was also more educated than the general population of the County of Los Angles, and had a higher average age. See table 1 below for additional information on sample characteristics.

Table 1. Demographic characteristics of sample by message group relative to the County of Los Angeles.

Characteristic	All	Social	Financial	Los Angeles County
Gender (% female)	50.1	44.9	56.9	50.3
Mean age [a] (SD)	53.6	54.2	52.8	34.4
Ethnicity				
African American	3.7	2.7	4.8	9.6
Asian / Asian American	10.4	9.4	11.0	11.1
Caucasian	65.7	66.7	64.4	38.7
Latino	11.2	11.0	11.5	48.5
Native American / Pacific Islander	0.6	0.8	0.5	0.8
Multiracial	5.6	6.7	4.3	4.6
Other	2.8	2.7	2.9	--
Educational Attainment (>=25 yrs)				
Less than High School	2.1	2.3	1.9	25.8
High school diploma	5.5	5.0	6.0	19.3
Technical/trade school	--	--	--	--
Some college / Associate's degree	24.1	27.5	20.0	24.1
4-year college degree	34.8	32.4	37.7	20.4
Graduate / professional degree	33.5	32.8	34.4	10.4

HS degree or higher				
Bach or higher	97.9	97.7	98.1	74.2
	68.3	65.3	72.1	30.8
Political Affiliation				--
Liberal	56.3	57.3	55.1	
Moderate	24.9	25.3	24.4	
Conservative	18.8	17.4	20.5	
Annual household income				Median household income: $49,745
<$25,000	12.9	11.5	14.5	
$25,001-$50,000	15.9	14.7	17.3	
$50,001-$75,000	18.7	21.2	15.6	
$75,001-$100,000	14.1	13.4	15.1	
>$100,000	38.3	39.2	37.4	
Home ownership rate	58.7	58.8	58.6	46.9
Home type				
Single Family Home	52.0	56.3	46.7	
Apartment/Condo	35.7	31.8	40.7	
Duplex, Triplex	6.5	6.1	7.0	
Townhouse	4.8	5.0	4.7	
Mobile Home	0.6	0.3	0.9	
Other	0.2	0.3	0.0	

Method: Procedures

All study procedures were approved by the USC Institutional Review Board, which oversees all human subjects research.

In May 2014, LADWP began mailing EV surveys to utility customers selected at random. The surveys included 47 questions about customers' perceptions and attitudes towards motor vehicles, including electric vehicles (specifically EVs). Surveys were accompanied by one of two versions of a cover letter that emphasized either social norms ("LA is going electric with electric vehicles") or financial benefits ("Save money with an electric vehicle") associated with EVs.

Surveys batches were mailed periodically throughout the summer of 2014; in total, LADWP mailed 25,314 survey invitations with the social and financial messaging versions of the cover letters evenly split at 12,567 each. We received 483 responses, for a response rate of approximately 0.02%. 265 social 218 financial

Respondents were informed that the survey would require 5-10 minutes to complete, and were given several weeks to respond. The mailer included a postage paid, pre-addressed return envelope.

See Appendix A for the Social and Financial versions of the cover letter.

See Appendix B for the survey.

5. Summaries of the results of the performance of the smart grid systems and technologies derived from lab tests, field tests, or grid-connected applications.

Means and standard deviations for key survey items are presented in table 2 below. We found that respondents had relatively favorable attitudes of EVs, which was marginally higher among the social group relative to the financial group. Individuals were willing to pay slightly more than $2000 extra for an EV relative to a gasoline vehicle. Respondents who received the financial message were willing to pay substantially more than were those who received the social message.

Relative to gasoline cars, the sample estimated EV maintenance costs to be about equivalent, fuel costs to be lower, and the purchase price to be higher. These responses did not differ substantially across message group.

Regarding beliefs about EV ownership, the sample agreed that driving an EV indicated they were socially responsible, doing the right thing, and to a lesser extent, a trendsetter for environmentally friendly technologies. Most respondents also believed that EVs were cutting edge technology that were associated with reduced environmental impact, and that driving an EV demonstrates that they care about the environment. These responses did not differ substantially across message group.

Table 2. Means and standard deviations of key questions by message group.

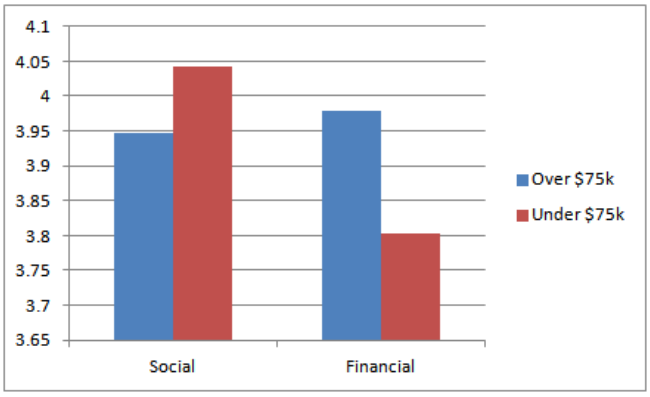
	Range	All	Social	Financial
General impression of EVs	1-5	3.9 (1.2)	4.0 (1.1)	3.8 (1.2)
Likelihood to buy/lease EV	1-10	5.4 (3.1)	5.4 (3.0)	5.5 (3.1)
Willingness to pay more for EV[a]	1-13	5.3 (3.4)	4.2 (3.4)	5.4 (3.4)
EVs demonstrate care about environment	1-7	5.1 (1.6)	5.1 (1.6)	5.2 (1.7)
EVs are cutting edge	1-7	5.1 (1.6)	5.1 (1.5)	5.1 (1.7)
EVs lessen environmental impact	1-7	5.4 (1.6)	5.3 (1.6)	5.4 (1.6)
Estimated purchase cost much more than gasoline car	1-5	3.8 (0.9)	3.8 (0.9)	3.8 (1.0)
Estimated fuel costs much more than gasoline car	1-5	1.8 (1.1)	1.8 (1.0)	1.9 (1.2)
Estimated maintenance costs much more than gasoline car	1-5	2.9 (1.2)	3.0 (1.1)	2.8 (1.3)
EV means doing right thing	1-7	5.0 (1.5)	5.0 (1.5)	5.0 (1.6)
EV makes me trendsetter	1-7	4.4 (1.6)	4.4 (1.6)	4.4 (1.6)
EV means I'm socially responsible	1-7	5.7 (1.1)	5.7 (1.1)	5.7 (1.1)

[a] Represents $0-$6000 in increments of $500 per scale point.

We also examined differences in responses by income category. We hypothesized that financial messaging would resonate more with individuals with incomes below the sample median ($75,000)

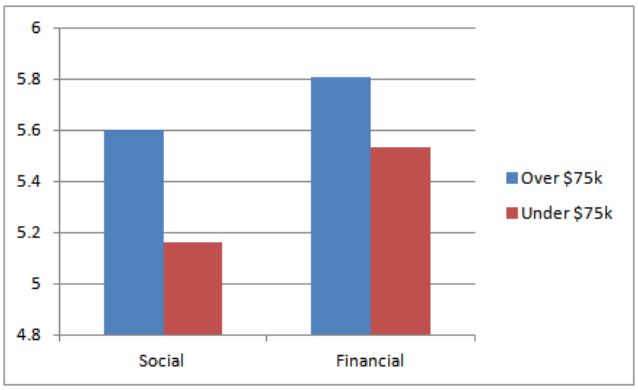
whereas social messaging would resonate more with those who had higher incomes. Results are reported below in figures 1 and 2.

Figure 1. Impression of EVs by message type and income group.



In looking at impression of EVs by message type and income group, we see that those who were below the sample's median income ($75,000) had somewhat lower ratings. However, among this group, those who received the social message had substantially more favorable impressions. No large difference was observed for individuals with higher than median incomes. This suggests that among those with relatively lower incomes, social messaging may promote EV acceptance more than financial messaging.

Figure 2. Likelihood to buy/lease EV as next vehicle.



When examining likelihood to select an EV as the next vehicle to purchase or lease, again those with incomes below the median reported lower likelihoods. However, among those with lower incomes, those who received financial messaging reported higher likelihoods than those who received social messaging. This indicates financial messaging may help boost intentions to purchase or lease EVs among those with lower incomes. This is the opposite of what we found for generally impression of EVs.

6. Summary of the major findings and conclusions, including lessons learned and best practices.

In summary,

Means and standard deviations for key survey items are presented in table 2 above. We found that respondents had relatively favorable attitudes of EVs, which was marginally higher among the social group relative to the financial group. Individuals were willing to pay slightly more than $2000 extra for an EV relative to a gasoline vehicle. Respondents who received the financial message were willing to pay substantially more than were those who received the social message.

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associated with reduced environmental impact, and that driving an EV demonstrates that they care about the environment. These responses did not differ substantially across message group.

In looking at impression of EVs and intentions to purchase or lease an EV, those who were below the sample's median income had somewhat lower ratings. However, among this subgroup, those who received the social message had substantially more favorable impressions, but reported lower likelihood of buying/leasing. These conflicting findings may indicate that social messaging works on a general attitudinal level, elevating general appraisals of
EVs. However, individuals have additional considerations when considering acquiring a vehicle, including financial resources. This may explain why financial messaging elevated likelihood of purchase intentions among those with lower incomes.

Limitations

The above findings should be viewed in light of several limitations. First, response bias must be considered. Individuals who elected to respond to the survey, particularly given its length, may differ in important ways from individuals who chose not to do so, such as pre-existing level of engagement or interest in energy or sustainability issues. This is a limitation common to self-report research, which relies on voluntary participation. Next, missing data owing to the self-report survey potentially introduced bias into findings (e.g., 18 % of sample did not provide income data); future analyses will use multiple imputation to estimate these missing values and increase effective sample size for more in-depth analyses. Further, although in many regards, the sample was representative of the Los Angeles community based on US Census data, there were several notable differences. These included racial makeup of the sample, mean age, and education level. The sample included a lower proportion of racial minorities, had a higher mean age, and a higher level of education relative to the general population of the County of Los Angeles. This somewhat limits the generalizability of the findings. In addition, the survey results do not capture the impact recent changes in fuel prices (due to the drop in oil prices) may have on EV acceptance and possible ownership. Finally, knowledge of the EV charging network, locations of charging stations, and charging rates were not captured in the survey.

Strengths

This study had a number of strengths. Although previous work has evaluated the impact of social influence messaging on low-cost, habitual pro-environmental behaviors, this is the first study to investigate the impact of social influence messaging on attitudes towards an infrequent, high-cost purchase. This is important area of inquiry because many energy efficiency measures (e.g., solar panel installation, new appliances) are infrequent with high-costs, and have the potential for considerable

energy savings. We also obtained both data on both self-reported (survey responses) and observed behavioral data (survey return rates).

Lessons Learned

Importance of maximizing participation

One of the limitations of this project was the low survey response rate. There were several contributors to this issue that could be avoided in future efforts.

Although the survey envelope was printed with stylized "Smart Grid L.A./Smart Power Partners," verbiage, it is possible that survey recipients were disinclined to open the envelope because its sender address was LADWP

The contents of the envelope may have appeared confusing and disorganized. The three pages (double sided) of the survey were folded, but not stapled, together. Other materials in the envelope included the cover letter, a return envelope, and a double-sided study information fact sheet. The impact of five pages of loose paper may have been off-putting to potential respondents.

The survey may have seemed time-consuming to answer, which also may have affected the response rate.

7. Summary of future plans and next steps with respect to additional testing, demonstration, or deployment

All study participants will be contacted again toward the end of the demonstration and asked to complete a follow-up survey, which will be similar to baseline survey in content, and will help identify changes in attitudes towards EVs and adoption rates over time. This data will be analyzed for further insights into Los Angelenos' perceptions and attitudes about EVs, which will help LADWP understand and plan for their impact on the grid.

8. Appendix: supporting documentation for reference

Appendix A

EV survey cover letter version 1: LA Is Going Electric With Electric Vehicles

Los Angeles Department of Water & Power

CHARGE UP!

→ LA is going electric with Electric Vehicle



Dear Customer

The Los Angeles Department of Water and Power (LADWP) would like to share with you some information about electric vehicles (EVs) in Los Angeles (LA). EVs are rapidly being adopted across LA and we want our customers to be informed about current trends. LADWP also requests your participation in a brief survey being conducted jointly with researchers at the University of Southern California (USC).

Smashing the Guinness World Record for the fastest cross-country trip made in EVs from LA to New York, the latest generation of EVs has set in motion a revolution in the car industry.

LA has proudly been at the forefront of the growing EV sensation all the way. According to the International Energy Agency, LA has the 2nd highest EV adoption rate and sales of any city on Earth, following San Francisco. Over the next five years, the LA area is predicted to remain in the top two for EV sales. In just one year's time, EVs will account for approximately 10% of automobiles purchased in the city – more than ever before. That means that by next year, on average, one of every five homes on your block could have an EV in the garage.

Angelenos love driving their EVs. Every ten seconds in LA, someone plugs their EV into the power grid to start charging. Given the sheer numbers of EVs, this is no surprise: LA is projected to have 80,000 registered plug-in vehicles by the end of 2015, and the Southern California region will have as many as 1 million by 2022.

There is no better time than now to understand this phenomenon that is sweeping LA. What makes LA residents the EV-loving pioneers we are? To better understand what makes Angelenos the proud leaders of the pack, LADWP has partnered with experts from USC to allow you the opportunity to have your opinion heard. This is a rare occurrence, so be sure to participate while you still can.

Please join your neighbors in helping LADWP out by filling out the enclosed brief survey. Please do the following:

1. Review the enclosed information sheet
2. Complete the enclosed survey form by July 25, 2014.
3. Enclosed with this letter is a pre-addressed, postage-paid envelope. Place your completed survey in this envelope and drop it in any mailbox. Send your envelope by to have your response counted July 25, 2014. You DO NOT need to affix postage to the envelope.

Thank you for your time! If you have any additional questions, please contact Smart Grid LA at 213-367-1971 or by email at SmartGridLA@ladwp.com.

Study ID: UP-14-00250 Valid From 4/28/2014 05/14

EV survey cover letter version 2: Save Money With An Electric Vehicle

Los Angeles Department of Water & Power

CHARGE UP!

→ Save Money with an Electric Vehicle



Dear Customer

The Los Angeles Department of Water and Power (LADWP) would like to share with you some information about electric vehicles (EVs) in Los Angeles (LA). LADWP customers who purchase EVs may be eligible for certain financial benefits and we want our customers to be informed about the current monetary advantages of EVs. LADWP also requests your participation in a brief survey being conducted jointly with researchers at the University of Southern California (USC).

How would you like to save money on car costs? Let's face it: no matter how much LA residents love their cars, they don't necessarily love paying for maintenance and the price at the pump. So how much does an average US household spend on gasoline each year? According to the U.S. Energy Information Administration, that number is approximately $3,000 / year. In contrast, the cost of the electricity required to power an electric vehicle (EV) to drive the same distance is $1,300 on average. **You read that correctly: the cost to fuel a conventional vehicle is more than double the cost to power an EV across the same distance.**

With gas prices rising every year, particularly in California, the US Department of Energy predicts that on average, gasoline will cost $3.67/ gallon by the end of this year. However, an eGallon will only cost $1.55/eGallon. An eGallon is the cost of fueling a vehicle with electricity compared to a similar vehicle that runs on gasoline, driving the same distance. As we mentioned above, gasoline is more than twice as expensive!

On top of that, if you say hello to an EV, you can say goodbye to many regular maintenance trips to the service shop. With fewer moving parts and engine fluids than a conventional car, less regular maintenance is required to keep an EV running smoothly. Saving you time at the shop and money at the pump, EVs are doing more than just getting you to where you need to go.

What is more, EVs purchasers in California may be eligible for an a rebate of up to $2,500 from the Clean Vehicle Rebate program. In addition, EVs purchased in or after 2010 may qualify for a federal income tax credit of up to $7,500, depending on the vehicle model. LADWP is also helping out with rebates on chargers and special EV rate pricing for charging at off peak times. With these incentives, and lower fuel and maintenance costs, EVs can reap you major financial benefits.

There is no better time than now to understand the effect of these advantages on people's opinions towards vehicles. To better understand what Los Angeles residents think about EVs and their benefits, LADWP has partnered with experts from USC to allow you the opportunity to have your opinion heard. This is a rare occurrence, so be sure to participate while you still can.

Please do the following:

1. Review the enclosed information sheet
2. Complete the enclosed survey form by July 25, 2014.
3. Enclosed with this letter is a pre-addressed, postage-paid envelope. Place your completed survey in this envelope and drop it in any mailbox. Send your envelope by to have your response counted July 25, 2014. You DO NOT need to affix postage to the envelope.

Thank you for your time! If you have any additional questions, please contact Smart Grid LA at 213-367-1971 or by email at SmartGridLA@ladwp.com.

Appendix B:

EV survey

Please complete and return this survey in the provided self-addressed stamped envelope by June 15, 2014.

To verify that you are a legal adult, in what year were you born? Please provide the 4-digit year (e.g., 1955): ___ ___ ___ ___

What is your primary address of residence?

_____ (e.g., 123 Main Street #103)

_____ (e.g., Los Angeles, CA 99999)

How long have you lived at the address printed above? _____ years

How would you describe your residence?

Single family home (detached or free-standing residence)

Townhouse

Multi-family home (apartment, condo)

Mobile home

Duplex, triplex, or 4-plex

Other (please specify) _____

Do you own or rent this residence?

Own

Rent

Other (please specify) _____

The scale below consists of a number of words that describe different feelings and emotions. Read each item and then check the box that most precisely indicates the extent you feel this way **at the present moment.** Do not think too much about this; respond with what comes to mind naturally.

	Very Slightly or not at all	A Little	Moderately	Quite a Bit	Extremely
Upset					
Hostile					
Alert					
Ashamed					
Inspired					
Nervous					
Determined					
Attentive					
Afraid					
Active					

Many of the following questions ask about electric vehicles. When we ask about electric vehicles (EVs), we are referring to all-electric vehicles (e.g., Nissan Leaf, Tesla Model S). We are **not referring to hybrid vehicles.**

What is your general impression of EVs?

Strongly Unfavorable	Somewhat Unfavorable	Neither Favorable Nor Unfavorable	Somewhat Favorable	Strongly Favorable

Think about your next vehicle purchase or lease. On a scale of 1 to 10, how likely are you to purchase or lease an EV?

1	2	3	4	5	6	7	8	9	10
Extremely Unlikely									Extremely Likely

Suppose you were interested in a car model that was also available in an all-electric vehicle. All other features of the vehicle are identical, but the EV costs more. How much extra would you be willing to pay for the EV compared to the conventional gas vehicle?

$0	$500	$1000	$1500	$2000	$2500	$3000	$3500	$4000	$4500	$5000	$5500	$6000

How many of the following vehicles automobiles are currently owned or leased by members of your household (including yourself)?

A conventional gasoline motor vehicle: _____

A battery hybrid (gasoline-electric) vehicle _____

A plug-in hybrid (gasoline-electric) vehicle _____

An all-electric vehicle (EV) _____

A fuel-cell vehicle _____

None of the above _____

Other (please specify) _____

On an average day, approximately how many miles do you drive in a car that you lease or own? Include trips made for work, school, shopping, errands, entertainment, etc.: _____miles

Do you have access to an electrical outlet where your car is parked at your primary residence?

No Yes

Please indicate the extent to which you agree or disagree with the following statements. Circle one answer per question.

Owning an EV will demonstrate to others that I care about the environment.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

EVs are at the cutting edge of technological transport innovation.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

Changing from a gasoline-powered vehicle to an EV will lessen my impact on the environment.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

After any tax credits, incentives, or dealer discounts, compared to a gasoline vehicle of the same type and size, do you think the purchase price of an EV is:

Much less	Somewhat less	About the same	Somewhat more	Much more

Compared to a gasoline vehicle of the same type and size, do you think the fuel costs of an EV are:

Much less	Somewhat less	About the same	Somewhat more	Much more

Compared to a gasoline vehicle of the same type and size, do you think the maintenance and repair costs of an EV are:

Much less	Somewhat less	About the same	Somewhat more	Much more

Approximately how many miles do you believe a fully-charged EV can drive before the battery is drained? _____miles

To what extent do you agree or disagree with the following statements? Circle one answer per question.

I would describe myself as environmentally responsible.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

I litter frequently.

Strongly Disagree | Disagree | Somewhat Disagree | Neutral | Somewhat Agree | Agree | Strongly Agree

I have purchased light bulbs that were more expensive but saved energy.

Strongly Disagree | Disagree | Somewhat Disagree | Neutral | Somewhat Agree | Agree | Strongly Agree

I have convinced members of my family or friends not to buy some products which are harmful to the environment.

Strongly Disagree | Disagree | Somewhat Disagree | Neutral | Somewhat Agree | Agree | Strongly Agree

I am concerned about the current environmental state the world is in.

Strongly Disagree | Disagree | Somewhat Disagree | Neutral | Somewhat Agree | Agree | Strongly Agree

I make an effort to recycle.

Strongly Disagree | Disagree | Somewhat Disagree | Neutral | Somewhat Agree | Agree | Strongly Agree

I like to fix cars.

Strongly Disagree | Disagree | Somewhat Disagree | Neutral | Somewhat Agree | Agree | Strongly Agree

I think the kind of car a person drives says something about the person.

Strongly Disagree | Disagree | Somewhat Disagree | Neutral | Somewhat Agree | Agree | Strongly Agree

Are you a member of an environmental, conservation or wildlife organization? (e.g. Nature Conservancy, Greenpeace, World Wildlife Federation, etc)

No Yes

Please indicate the extent to which each of the following statements is true for you.

I am confident that I could deal efficiently with unexpected events.

Not at all true Hardly True Moderately True Exactly True

Thanks to my resourcefulness, I know how to handle unforeseen situations.

Not at all true Hardly True Moderately True Exactly True

I can remain calm when facing difficulties because I can rely on my coping abilities.

Not at all true Hardly True Moderately True Exactly True

If I am in trouble, I can usually think of a solution.

Not at all true Hardly True Moderately True Exactly True

I can usually handle whatever comes my way.

Not at all true Hardly True Moderately True Exactly True

To what extent are you concerned about air pollution in your city?

Completely Unconcerned | Unconcerned | Somewhat Unconcerned | Neutral | Somewhat Concerned | Concerned | Extremely Concerned

How serious a threat is climate change to humankind?

Not At All Serious | Not Serious | Not Very Serious | Neutral | Somewhat Serious | Serious | Very Serious

How well is climate change understood by science?

Not Understood At All	Not Understood	Not Well Understood	Neutral	Understood	Well Understood	Very Well Understood

How much does the idea of climate change fill you with dread?

No Dread At All	No Dread	Not Much Dread	Neutral	Some Dread	Dread	A Lot of Dread

To what extent do you have moral concern about climate change?

No Moral Concern At All	No Moral Concern	Not Much Moral Concern	Some Moral Concern	Moral Concern	Strong Moral Concern	Very Strong Moral Concern

Driving an EV means that:

I am doing the right thing

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

I am a trendsetter for environmentally friendly technologies

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

I am socially responsible

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

Tell us about yourself. As with all questions in this survey, you may skip any questions you prefer not to answer

What is your gender?

Male Female

What do you consider to be your political orientation?

Very Liberal Liberal Somewhat Liberal Moderate Somewhat Conservative Conservative Very Conservative

With which ethnic category do you most strongly identify? Circle only **one option.**

African or African American Asian or Asian American Caucasian/ White Latino/a Native American / Pacific Islander Multiracial Other (please specify) _____

What is your annual household income? As with all questions in this survey, you may skip this question if you prefer not to answer.

Under $25,000 $25,000 - $50,000 $50,001-$75,000 $75,001-$100,000 More than $100,000

Please indicate your highest level of education (include degree you are currently working on if applicable).

Did not complete high school High school / GED Some college / associate's degree 4-year college degree Graduate degree

May the Lead USC Researcher, Dr. Nicole Sintov, contact you in the future to inquire about your attitudes towards motor vehicles?

No Yes

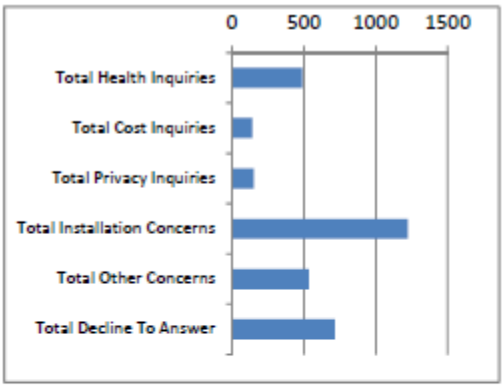
If yes, please provide phone number: (____ ____ ____) ____ ____ ____ - ____ ____ ____ ____

Appendix J Smart Grid LA Call Log, Final Customer Inquiry Data Report

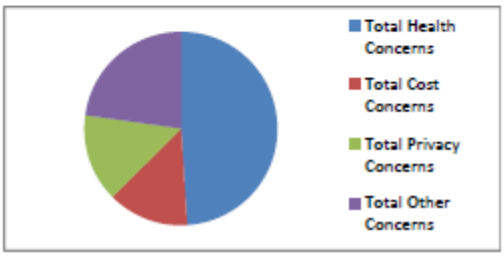
SUMMARY OF SMART METER INQUIRIES TO SMART GRID LA	
INQUIRY TOTALS	
Requested Opt-Out Inquiries (Unresolved)	0
Installation Date Inquiries (Unresolved)	0
Meter Spec Inquiries (Unresolved)	0
Other Inquiries (Unresolved)	4
Confirmed Opt-Outs (SGRDP)	1120
Confirmed Opt-Outs (Non-SGRDP)	404
Resolved Install Inquiries	1588
Other Inquiries (Resolved)	349
Total Inquiries to Smart Grid LA	**3465**
Total Resolved Inquiries to Smart Grid LA	**3461**
Total Unresolved Inquiries to Smart Grid LA	**4**

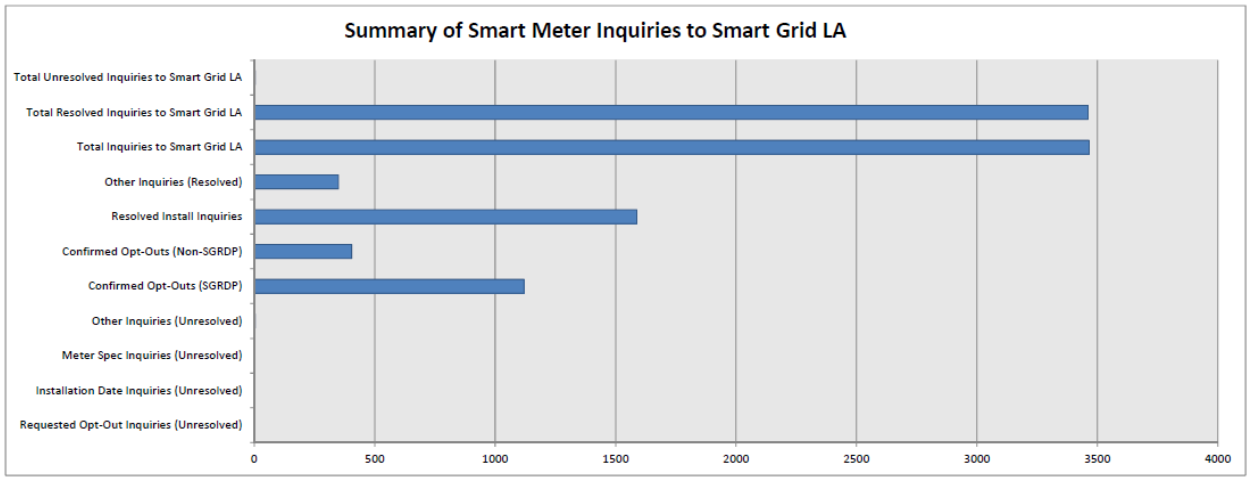
Total Inquiries Forwarded from CCC	**591**
Total Percentage Inquiries from CCC	**0.17**

TYPES OF INQUIRY TO SGRDP PROGRAM INQUIRIES	
Total Health Inquiries	490
Total Cost Inquiries	142
Total Privacy Inquiries	149
Total Installation Concerns	1223
Total Other Concerns	533
Total Decline To Answer	713
Total Concerns Collected	**2537**



REASONS FOR SGRDP & NON-SGDP OPT-OUTS	
Total Health Concerns	49.0%
Total Cost Concerns	13.6%
Total Privacy Concerns	14.7%
Total Other Concerns	22.8%
Total Opt-Out Concerns	**966**





TOTAL RESOLVED SMART METER INQUIRIES TO SMART GRID LA

OPT-OUT INQUIRIES		INSTALL INQUIRIES		NON-SGRDP OPT-OUT INQUIRIES		OTHER INQUIRIES	
Total Opt-Outs Inquiries	1120	Total Install Inquiries	1588	Total Non-SGRDP Opt-Out Inquiries	404	Total Customer Inquiries	349
Total Resolved Inquiries to Smart Grid LA	**3461**						

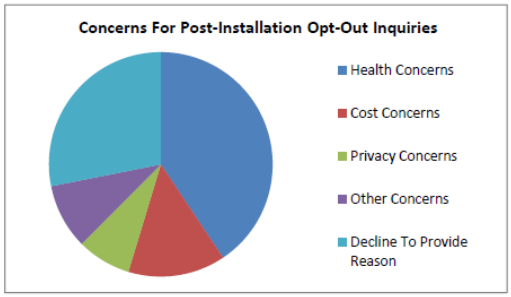
CONCERNS FOR OPT-OUT INQUIRIES*		CONCERNS FOR INSTALL INQUIRIES*		CONCERNS FOR NON-SGRDP OPT-OUT INQUIRIES*		CONCERNS FOR OTHER INQUIRIES*	
Health Concerns	271	Health Concerns	1	Health Concerns	202	Health Concerns	15
Cost Concerns	111	Cost Concerns	1	Cost Concerns	20	Cost Concerns	10
Privacy Concerns	110	Privacy Concerns	3	Privacy Concerns	32	Privacy Concerns	4
Other Concerns	163	Installation Concerns	1223	Other Concerns	57	Other Concerns	311
Decline To Provide Reason	621	Decline To Provide Reason	0	Decline To Provide Reason	92	Decline To Provide Reason	0
Total	655	Total	1228	Total	311	Total	340
Total Health Concerns	**489**						
Total Cost Concerns	**142**						
Total Privacy Concerns	**149**						
Total Other Concerns	**531**						
Total Decline To Provide Reasons	**713**						
Total Concerns	**1311**						

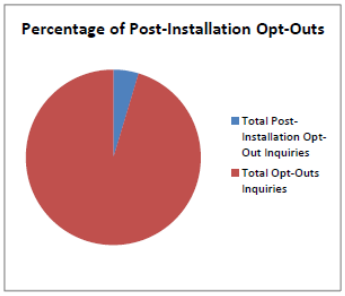
AREA INFO FOR OTHER INQUIRIES	
SGRDP Area Inquiries	198
Non-SGRDP Area Inquiries	137
Total	335

**Customers can provide multiple reasons for opting out.*

POST-INSTALLATION OPT-OUT INQUIRIES*	
Total Post-Installation Opt-Out Inquiries	55
Total Opt-Outs Inquiries	1120
Percentage of Post-Installation Opt-Outs	4.91%

CONCERNS FOR POST-INSTALLATION OPT-OUT INQUIRIES*	
Health Concerns	26
Cost Concerns	9
Privacy Concerns	5
Other Concerns	6
Decline To Provide Reason	18
Total	64





TOTAL UNRESOLVED SMART METER INQUIRIES TO SMART GRID LA							
OPT-OUT INQUIRIES		**INSTALL INQUIRIES**		**METER SPECS INQUIRIES**		**OTHER INQUIRIES**	
Opt-out Request by Phone	0	Opt-out Request by Phone	0	Opt-out Request by Phone	0	Opt-out Request by Phone	3
Opt-out Request by Email	0	Opt-out Request by Email	0	Opt-out Request by Email	0	Opt-out Request by Email	1
Opt-out Request by Letter	0	Opt-out Request by Letter	0	Opt-out Request by Letter	0	Opt-out Request by Letter	0
Total	**0**	**Total**	**0**	**Total**	**0**	**Total**	**4**
Total Unresolved Inquiries to Smart Grid LA	**4**						

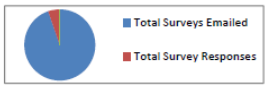
CONCERNS FOR OPT-OUT INQUIRIES*		**CONCERNS FOR INSTALL INQUIRIES***		**CONCERNS FOR METER SPECS INQUIRIES***		**OTHER CUSTOMER INQUIRIES***	
Health Concerns	0	Health Concerns	0	Health Concerns	0	Health Concerns	1
Cost Concerns	0	Cost Concerns	0	Cost Concerns	0	Cost Concerns	0
Privacy Concerns	0	Privacy Concerns	0	Privacy Concerns	0	Privacy Concerns	0
Other Concerns	0	Installation/Other Concerns	0	Other Concerns	0	Other Concerns	2
Total	**0**	**Total**	**0**	**Total**	**0**	**Total**	**3**
Total Health Concerns	**1**						
Total Cost Concerns	**0**						
Total Privacy Concerns	**0**						
Total Other Concerns	**2**						
Total Concerns	**3**						

**Customers can provide multiple reasons for opting out.*

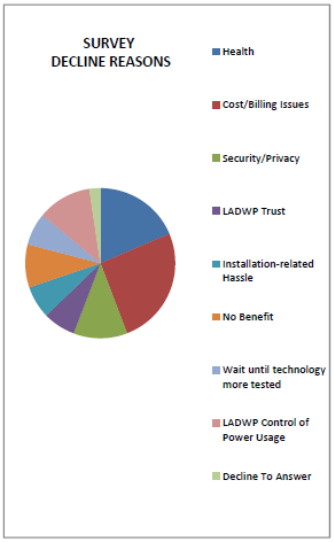
AREA INFO FOR OPT-OUT INQUIRIES		**AREA INFO FOR INSTALL INQUIRIES**		**AREA INFO FOR METER SPECS INQUIRIES**		**AREA INFO FOR OTHER INQUIRIES**	
SGRDP Area Inquiries	0	SGRDP Area Inquiries	0	SGRDP Area Inquiries	0	SGRDP Area Inquiries	0
Non-SGRDP Area Inquiries	0	Non-SGRDP Area Inquiries	0	Non-SGRDP Area Inquiries	0	Non-SGRDP Area Inquiries	2
Total	**0**	**Total**	**0**	**Total**	**0**	**Total**	**2**

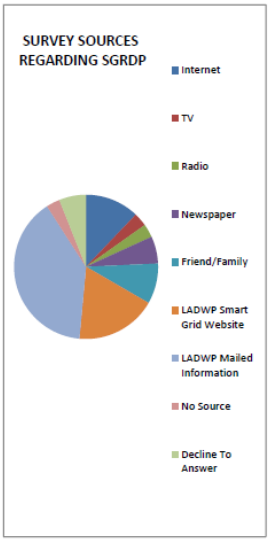
SGRDP OPT-OUT SURVEY RESPONSE RESULTS

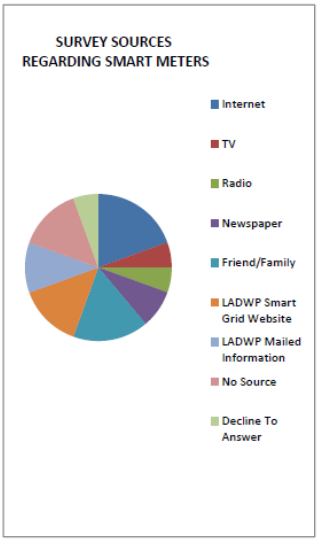
Survey Return Percentage	
Total Surveys Emailed	381
Total Survey Responses	21
Percentage of Returned Surveys	5.51%

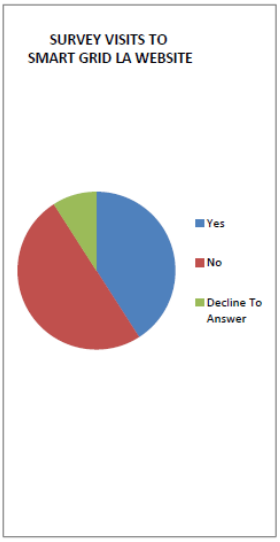


1. Why are you choosing to decline the LADWP Smart Power Partners program?		2. From what source did you receive your information regarding this program?		3. From what source did you receive your information regarding smart meters in general?		4. Have you visited the Smart Grid LA website (www.ladwp.com/smartgrid)?	
Health	8	Internet	4	Internet	7	Yes	9
Cost/Billing Issues	11	TV	1	TV	2	No	11
Security/Privacy	5	Radio	1	Radio	2	Decline To Answer	2
LADWP Trust	3	Newspaper	2	Newspaper	3	Total	22
Installation-related Hassle	3	Friend/Family	3	Friend/Family	6		
No Benefit	4	LADWP Smart Grid Website	6	LADWP Smart Grid Website	5		
Wait until technology more tested	3	LADWP Mailed Information	13	LADWP Mailed Information	4		
LADWP Control of Power Usage	5	No Source	1	No Source	5		
Decline To Answer	1	Decline To Answer	2	Decline To Answer	2		
Total	43	Total	33	Total	36		





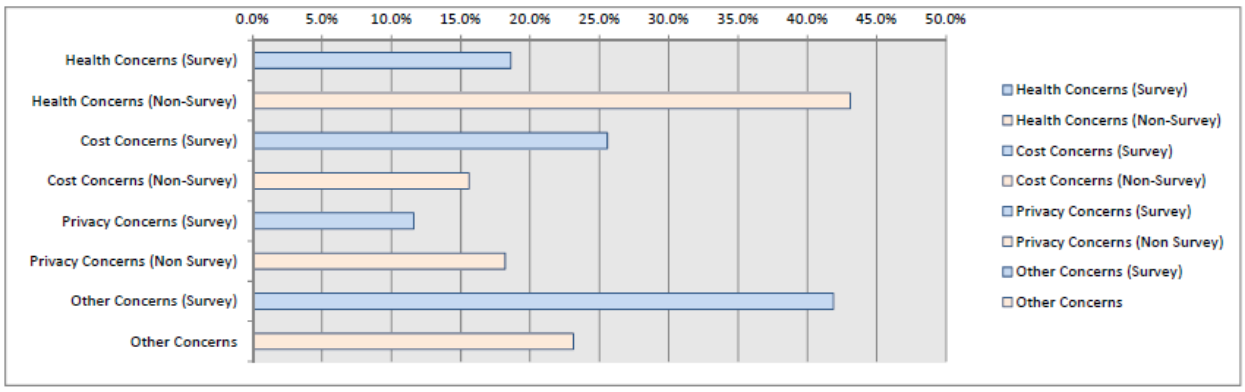




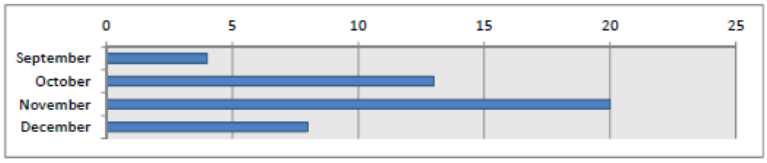
NON-SURVEY FEEDBACK: REASONS FOR SGRDP & NON-SGDP OPT-OUTS	
Health Concerns	43.1%
Cost Concerns	15.6%
Privacy Concerns	18.2%
Other Concerns	23.1%
Total Concerns	731

SURVEY FEEDBACK: REASONS FOR SGRDP & NON-SGDP OPT-OUTS	
Health Concerns (Survey)	18.6%
Cost Concerns	25.6%
Privacy Concerns	11.6%
LADWP Trust (Other)	7.0%
Installation-related Hassle (Other)	7.0%
No Benefit (Other)	9.3%
Wait until technology more tested (Other)	7.0%
LADWP Control of Power Usage (Other)	11.6%
Total Concerns	43

COMPARISON OF SURVEY VS NON-SURVEY REASONS FOR SGRDP & NON-SGDP OPT-OUTS	
Health Concerns (Survey)	18.6%
Health Concerns (Non-Survey)	43.1%
Cost Concerns (Survey)	25.6%
Cost Concerns (Non-Survey)	15.6%
Privacy Concerns (Survey)	11.6%
Privacy Concerns (Non Survey)	18.2%
Other Concerns (Survey)	41.9%
Other Concerns	23.1%



High Bill Inquiries To Smart Grid 2013	
September	4
October	13
November	20
December	8
Total High Bill Inquiries	**45**



Appendix K Voluntary Curtailment Experiments Among USC Microgrid Office Dwellers Summary Report

Voluntary Curtailment Experiments Among USC Microgrid Office Dwellers Summary Report

Los Angeles Department of Water and Power Smart Grid Regional Demonstration Program

Customer Behavior Project

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1. Change History

a. Author(s): Nicole Sintov

b. Reviewer/Approvers: Adam Chhan

2. Executive Summary

The availability of real-time data has made possible new options for building energy management, including real-time feedback on energy use, alerts, and demand response capabilities. These new technologies can be combined with empirically validated social science approaches to develop engaging and effective energy management strategies. The primary goal of this study was to examine the effectiveness of different message appeals on participation in demand response events. USC University Park Campus employees participated in the study. The source of the message appeals varied across participants, who were randomly assigned to one of three groups: 1) Control messaging, 2) Anthropomorphized messaging- 1st person (Anthro 1st), and 3) Anthropomorphized messaging- 3rd person (Anthro 3rd). Participants received email messages encouraging their participation in a) Demand Response (DR) events and b) brief online surveys that followed each DR event. Building-level electricity use and survey responses regarding DR event participation constituted the study outcomes.

Across the two DR events, 64-78% of survey respondents indicated that they participated in the DR event. On average, respondents participated in the event for 1-2 hours of the three-hour events. Across the samples, the mean level of participation was mid-range and did not vary significantly by condition, though the trend was in the expected direction, with highest ratings among the Anthro 1st condition and lowest ratings among Controls. Participants also reported the likelihood that they would participate in future DR events. Mean ratings were rather high, and varied across groups in the expected direction, though group differences were not statistically significant. When making a dichotomous comparison between both anthropomorphism conditions versus control, differences were marginally significant.

There were no significant differences in adjustments of thermostat, air conditioning, or space heater by the three conditions. However, the total number of non-equipment behaviors undertaken to save energy during the event did vary across study groups. The Anthro 1st group perfumed the greatest number (M=4.5), followed by Controls (M=3.8), and finally Anthro 3rd (M=3.5). The contrast between the Anthro 3rd and Control groups was not statistically significant, whereas the contrast between Anthro 1st and Anthro 3rd was.

Regarding barriers and motivators to participation, we found that over half of those who participated stated that they did so because they felt strongly about conservation, and nearly half reported that participation was important to the building. Those who did not participate most commonly cited as barriers that productivity would be affected, uncertainty about what actions to take, or that others in the workstation needed equipment. Notably, no participant cited lack of comfort as a reason for not participating, and few reported receiving the notice too late, suggesting that the notice timing was appropriate.

In conclusion, participation in the preceding event was not enhanced by anthropomorphic messaging, but number of behaviors performed and willingness to participate in the future were. This suggests a nuanced effect whereby anthropomorphic messages differentially impact type of behavior. Among those who have elected to participate, anthropomorphic messaging propels additional change, but it may not have an effect on encouraging participation in the first place. In this sense, it may serve as a performance enhancer. The knowledge gained from this research project contributes to the literature on persuasion, anthropomorphism, and energy efficiency.

3. An overview of the Demonstration

a. Smart grid capabilities and functions demonstrated

The present study demonstrated the following functions from the SOPO:

1. Demonstrate the impact of smart grid communication systems and processes on customer usage patterns.

2. Demo effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns.

3. Demo communication and media content on Smart Grid deployment, incorporating changes observed in awareness, attitudes, and energy use behaviors.

b. Smart grid impacts and benefits demonstrated

Electric power interruptions are associated with significant economic consequences, with annual losses ranging from €150 among European Union businesses to $80 billion among the United States economy (Lawrence Berkeley National Laboratory, 2004) to 6-20% of commercial sales lost among African nations. Electric utilities allocate considerable resources to avoiding interruptions. Toward this end, each year

utilities are investing $700 million in demand response (DR) strategies to curtail peak load as alternatives to bringing on additional generation, which is environmentally and economically costly (US Energy Information Administration, 2013).

DR forecasting models predict when, where, and how much energy will be used, but solving the key problem of how to ultimately reduce demand requires programs that encourage electric customers to make real-time, voluntary behavioral changes to curtail energy use during peak hours. The US Federal Energy Regulatory Commission characterizes DR as a “bottom-up process…driven by changes in customer behavior”. A number of white papers suggest that such programs, many of which offer small monetary incentives, can be effective in reducing peak demand. However, the majority of programs have not been evaluated, and methodological limitations among those that have suggest areas for improvement.

Social science approaches must be leveraged to improve these efforts. Decades of research support the effectiveness of various tools in changing end-user behaviors to ultimately reduce overall household energy use. However, the optimal tools for promoting continuous, long-term energy conservation may differ from those that can support discrete, time-delimited behavior change. Persuasive messaging can be a cost-effective, time-sensitive strategy for promoting participation in DR events. Additionally, persuasion remains one of the more complex and interesting domains within social psychological research (Cialdini, 2001). Discovering how to shift behavior is a primary focus not only of academics, but most recently with their influential book, "Nudge", Thaler and Sunstein make a case that policy makers stand to gain much from experimental data. Past research has shown that people have a propensity to make meaning of their world, and will sometimes anthropomorphize non-human agents as a way to make sense of an otherwise confusing object (Waytz et al., 2010). If an appeal to reduce energy does not convince end-users to perform a given behavior, or seems too steep of a request) might the introduction of anthropomorphized figure persuade them? Perhaps by making a case that the building needs a break or is overworked, users might come to understand the need to reduce their energy use. This is the concept we tested in the present study.

c. List of objectives/Scope

The primary goal of this study was to examine the effectiveness of different messaging appeals in reducing energy use during demand response (DR) events in a university context. The source of the message appeals varied across participants to include anthropomorphized first person appeals, anthropomorphized third person appeals, and non-anthropomorphized third person appeals. We hypothesized that the first person anthropomorphized messages would produce the highest compliance rates and higher engagement in energy-saving activities, followed by the third person anthropomorphized messages.

d. Mapping to the SOPO & Deliverables

The following deliverables from the SOPO are presented in this report:

1. Identification of the effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns.

2. Identification of the key socio-demographic and community structure variables in the Smart Grid adoption process.

3. Identification of the key decision factors in the adoption of Smart Grid related technologies.

4. Integration of behavioral and social factors into the design and implementation of Smart Grid information architecture, data management, and cyber-security systems.

5. Deliver comprehensive data, analysis, and models relating socio-demographic compositions and customer use types to Smart Grid technology acceptance and use patterns.

6. Periodic reports documenting the results of the demonstration.

4. Descriptions of the methodologies utilized

Method

Participants

Approximately 50 buildings on the University Park Campus were targeted for participation in the study. Deans of the relevant departments within each building were contacted to inform them about the project, provide the opportunity to answer questions, and request email addresses for all faculty and staff in their departments. Deans across 41 buildings provided usable email addresses for 3299 employees. Individuals who responded to study emails indicating they did not wish to participate were addressed on a one-on-one basis and removed from the study. A $500 visa gift card was raffled off as an incentive for responding to the surveys.

Eligibility. Individuals could participate in the study if they were University of Southern

California employees who had an office in one of the 50 target buildings and were over the age

of 18. Eligibility was determined by survey responses.

The sample was predominantly middle-aged, and slightly less than two-thirds of participants were female. Participants reported identifying more with liberal political orientation. They reported considerable tenures both at USC and in their current office building. See table 1 below for details.

Table 1. Participant background characteristics.

	Mean (SD)
Age	39.2 (13.0)
Political orientationa	27.8 (22.8)
Average number of hours spent in office per day	8.1 (1.8)
Total number of years at USC	8.6 (8.4)
Total number of years in current building	6.3 (6.1)
Gender (% male)	36

aRated on a sliding scale from 1-100 with “liberal” coded as 0 and “conservative” coded as 1. 36

Procedures

All study procedures were approved by USC IRB. A study email account was created (USC Save Power Events Team) to handle all communications related to the study. The 3299 employees received several email messages from this account. They were randomly assigned to one of three experimental groups:

1. Control (Control)
2. Anthropomorphism - 3rd person (Anthro 3rd)
3. Anthropomorphism - 1st person (Anthro 1st)

For each DR event, four Notifications were emailed to the 3299 individuals. See Appendix A for copies of all Notifications:

1. The first message introduced the "Save Power Event" program and was emailed to potential participants approximately one week prior to the scheduled DR event. The message introduced the program, explained what was being asked of participants, and provided tips for saving energy during DR events.

2. The second message alerted participants about a Save Power Event occurring the following day and requested their participation. Animated images of buildings were included in the message and varied across the study groups.

3. The third message notified participants that a Save Power Event would begin in the next hour and requested their participation. Animated images of buildings were included in the message and varied across the study groups.

4. The last message asked participants to respond to an online survey that assessed involvement in the DR event.

In summary, all potential participants received three recruitment messages asking for their participation in the voluntary DR event. They could choose whether or not to take part in the event by engaging in any energy conservation behavior of their choice. The fourth message, which followed the DR event, requested participation in a brief online survey. In this study, self-reported participation in the post-DR survey confirmed participation. Note that Notifications 2 and 3 contained the experimental manipulations, which included both text and image manipulations.

Manipulation check. The survey included a manipulation check to test whether participants recalled the experimentally manipulated messaging in Notifications 2 and 3. Results showed that 73% of controls were accurate, with lower accuracy rates for both Anthropomorphism conditions. Specifically, 46% of Anthro 3rd and 57% of Anthro 1st participants were correct, but 80% and 81%, respectively, recalled that the message was anthropomorphized in some manner. This suggests that the anthropomorphism manipulations were distinguished clearly from control conditions, but perhaps not between themselves.

Materials

Recruitment materials. The recruitment materials are described above (Notification emails 1, 2, and 3). All recruitment materials are provided in Appendix A.

Follow-up survey. Following each DR event, potential participants were emailed a link to an online survey and asked to respond. The survey required approximately 3 minutes to complete and was available 24

hours per day, 7 days per week for one week after the end of each DR event. An online survey assessed participation in the preceding DR event, factors associated with the decision of whether or not to participate, comfort during the DR event, and likelihood of participating in future DR event. Surveys were hosted by Qualtrics, a secure software commonly used by university researchers. Individuals viewed an IRB-approved information sheet prior to viewing survey questions. See Appendix B for survey items.

5. Summaries of the results of the performance of the smart grid systems and technologies derived from lab tests, field tests, or grid-connected applications.

Based on Event #1, from the original survey sample of n=206, one response was deleted due to a repeat Internet Protocol (IP) address, 26 responses were dropped because no data were provided, and six cases were dropped because the respondents indicated they did not currently work in a USC building. Fewer responses were obtained for the survey following Event #2 (n=130). Approximately 64% of Survey #2 respondents reported participating in DR Event #2. The overall pattern of results for Event #1 was replicated for Event #2. This replication of results is a positive finding that places confidence in the reliability of the results. To avoid redundancy in this summary report, below we focus on data from the first event. The small sample size precluded cross-lag modeling due to inadequate statistical power.

Participation and Subjective Effort

A total of 78% of survey participants indicated that they participated in the first DR event. On average, respondents participated in the event for 1-2 hours. To approximate subjective participation, respondents were asked to report their "level of participation" in the event on a scale from 1 (Not at all) – 7 (Very Much). Across the sample, the mean level of participation was 4.07. The means varied across groups in the expected direction, but was not statistically significant, $F(2, 171)=0.39$, $p=.67$, nor was a dichotomous comparison of both anthropomorphism messages versus the control, $F(1, 172)=0.68$, $p=.41$. Therefore, whereas this finding does not serve as evidence of true group differences, it points to a general trend that may have been substantiated by a larger sample size. See Figure 1 for details.

Participants also reported level of effort exerted during the DR event. The sample-wide mean was 2.47 on a scale from 1 (none at all) to 5 (a lot), and no differences were observed across the three conditions, $F(2, 119)=0.65$, $p=.52$. Nor was the dichotomous comparison of both anthropomorphism groups combined versus the control, $F(1, 120)=1.03$, $p=.31$. This question was asked towards the end of the survey, potentially contributing to the decrease in sample size. The fact that only 136 individuals across 50 buildings reported participating in the event, an average of 2.7 respondents per building, precluded detection of meaningful changes in building-level energy use. The efforts made by participants

unfortunately were “diluted” by their fellow building occupants who did not participate, thereby masking their efforts.

Figure 1. Perceived level of effort exerted during DR event #1.

Willingness to Participate in the Future

Participants reported the likelihood that they would participate in future DR events on a scale from 1 (very unlikely) to 7 (very likely). The mean rating was rather high (5.88), and varied across groups in the expected direction, though group differences were not statistically significant. When making a dichotomous comparison between both anthropomorphism conditions versus control, the difference was marginally significant, $F(1, 122)=2.78$, $p=.098$. See figure 2 below for a visual representation of the findings.

Figure 2. Likelihood of participation in future DR events following DR event #1.

Behaviors Performed

Participants indicated specifically which behaviors they performed during DR events. First, they were presented with a list of various mechanical equipment (thermostat, air condition, space heater) and were asked to indicate what adjustments, if any, they had made during the DR event. Only 40 who had thermostats in their workstations, and just over half (n=23) stated they had control over their thermostat. A total of 14 respondents reported the presence of air conditioning wall units, yet less than half of them (n=6) reported having control over these units. Nearly all respondents who stated they had space heaters said they had control over the units (n=24). There were no significant differences in adjustments of thermostats, air conditioning units, or space heaters by the three conditions, ($p=.23$, $p=.56$, $p=.57$ respectively). Similarly, comparing the both anthropomorphism groups to the control group for thermostat, air conditioning and space heater adjustments yielded non-significant differences ($p=.38$, $p=.26$, $p=.37$ respectively).

In an effort to not limit participants’ energy conserving behaviors, participants were presented with a list of 17 additional behaviors (coded yes/no) that did not involve equipment adjustments (e.g. put on an additional layer of clothing). A total score was computed for each participant and then compared across condition. Of the 118 participants who provided data, participants performed an average of 3.91 (2.06)

behaviors, ranging from 1-12. The most common behaviors were turning off lights, powering down larger office equipment such as copy machines, and putting devices in sleep mode. In comparing the three conditions, the number of behaviors performed was marginally different across groups, $F(2,115)=2.75$, $p=.07$. This omnibus test tells us that the three groups differed marginally from one another. Regarding differences among specific groups, contrast analyses reveal that the number of behaviors performed was significantly higher among participants in the Anthro 1st group ($M= 4.5$ $SE=.32$) relative to the Anthro 3rd group ($M=3.5$ $SE=.32$) , $p=.02$. Differences between the Anthro 1st group and the control ($M=3.8$ $SE=.33$) were not statistically different from one another, $p=.13$, nor were they different between Anthro 3rd and control, $p=.47$. See figure 3 and table 2 below for details.

Figure 3. Number of additional behaviors performed during DR event #1.

Table 2. Behaviors undertaken during DR event #1.

Behavior performed	% of respondents
Turned off lights that were not in use	68%
Put devices in sleep mode	50%
Turned off office devices (e.g., copy machine)	40%
Encouraged others in my office to participate	27%
Got a cold beverage	18%
Unplugged devices (e.g., computers)	18%
Adjusted window shades to block sun	17%
Removed a layer of clothing	16%
Put on an additional layer of clothing	13%
Adjusted window shades to allow sun in	12%

Got a hot beverage 9%

Opened Window 9%

Adjusted thermostat 8%

Turned off lab equipment 5%

Closed Window 3%

Motivators and Barriers to DR Participation

Participants also answered questions about their reasons for participating, or not participating, in the DR event. The response selections and endorsement frequencies are listed below in Tables 4a and 4b. Over half of those who participated stated that they did so because they felt strongly about conservation, and nearly half reported that participation was important to the building. Those who did not participate most commonly cited as barriers that productivity would be affected, uncertainty about what actions to take, or that others in the workstation needed equipment. Notably, no participant cited lack of comfort as a reason for not participating, and few reported receiving the notice too late, suggesting that the notice timing was well-structured, and concerns over comfort did not act as a barrier to participation in the present study.

Table 3a. Self-reported reasons for participating in DR Event #1.

Reason n

Feel strongly about conservation 76

Important to building 60

Others were participating 15

Thought it was mandatory 5

Other 16

Table 3b. Self-reported reasons for not participating in DR Event #1.

Reason n

Productivity would be affected 9

Not sure what actions to take 7

Others in workstation needed equipment 7

Distracted 5

Inconvenient 4

Received notice too late3

Didn't think actions would help 2

Not important 2

Uncomfortable 0

Other 14

Perceived Control and DR Event Participation

We reasoned that some participants might have the intentions to reduce their consumption but might not have sufficient control or authority within their workstation to do so, we assessed perceived control and ran correlations with relevant variables. A key finding was that subjective participation and perceived control were highly related ($r=.49$, $p<.001$), meaning that the more participants felt they could control energy use in their workstations, the higher their level of subjective participation in the event. We also assessed participants' ability to control their environments: surveys specifically prompted participants to provide the number of equipment items they felt that they had control over and were at liberty to adjust. A total number of controllable equipment was computed for each participant. The relationship between actual equipment control and subjective participation was significant, $r=.23$, $p=.01$. This suggests that enhancing both actual and perceived control are important for promoting participation in DR programs.

6. Summary of the major findings and conclusions including lessons learned and best practices.

Across the two DR events, 64-78% of survey respondents indicated that they participated in the DR event. On average, respondents participated in the event for 1-2 hours of the three-hour events. Across the samples, the mean level of participation was mid-range and did not vary significantly by condition, though the trend was in the expected direction, with highest ratings among the Anthro 1st condition and lowest ratings among Controls. Participants also reported the likelihood that they would participate in future DR events. Mean ratings were rather high, and varied across groups in the expected direction, though group differences were not statistically significant. When making a dichotomous comparison between both anthropomorphism conditions versus control, differences were marginally significant.

There were no significant differences in adjustments of thermostat, air conditioning, or space heater by the three conditions. However, the total number of non-equipment behaviors undertaken to save energy during the event did vary marginally across study groups. The Anthro 1st group perfumed the greatest number (M=4.5), followed by Controls (M=3.8), and finally Anthro 3rd (M=3.5). The contrast between the Anthro 3rd and Control groups was not statistically significant, whereas the contrast between Anthro 1st and Anthro 3rd was.

Regarding barriers and motivators to participation, we found that over half of those who participated stated that they did so because they felt strongly about conservation, and nearly half reported that participation was important to the building. Those who did not participate most commonly cited as barriers that productivity would be affected, uncertainty about what actions to take, or that others in the workstation needed equipment. Notably, no participant cited lack of comfort as a reason for not participating, and few reported receiving the notice too late, suggesting that the notice timing was appropriate.

Finally, we found that subjective participation was positively related to measures of both perceived control and actual control, suggesting that enhancing both actual and perceived control are important for promoting participation in DR programs. Programs may enhance perceived control in various ways, for instance, by using training programs to provide participants with the requisite skills to make adjustments to equipment or office programs that foster a sense of ownership over personal comfort parameters.

In conclusion, participation in the preceding event was not enhanced by anthropomorphic messaging, but number of behaviors performed and willingness to participate in the future were. This suggests a nuanced effect whereby anthropomorphic messages differentially impact type of behavior. Among those who have elected to participate, anthropomorphic messaging propels additional change, but it may not have an effect on encouraging participation in the first place. In this sense, it may serve as a performance enhancer.

Limitations

The above findings should be viewed in lights of several limitations. First, response bias must be considered. Individuals who elected to participate in the surveys may differ in important ways from individuals who chose not to participate, such as pre-existing level of engagement or interest in energy or sustainability issues. Although we used the gift card raffle in an attempt to recruit a broader sample, it is possible that results may not generalize to all populations. In addition, our sample size was relatively small.

We identified a number of promising trends, but most tests did not reach traditional levels of statistical significance. As well, detection of changes in building energy was not possible given the small sample. This underscores the importance of recruitment efforts in these types of studies.

Strengths

This study had a number of strengths. First, to our knowledge, it was the first experimental study of a workplace-based DR program. This work has therefore contributed to current understanding on the effectiveness of energy programs in commercial settings. Second, the study used an experimental design. To date, no published DR study has employed a true experimental design. Non-experimental designs provide useful information, but they are limited by the types of the conclusions that can be drawn about the strategies employed. The current project has therefore advanced knowledge regarding the impact of persuasive messaging variants on participation in DR events.

Lessons Learned

- Recruit, recruit, recruit
    - As mentioned, one of the limitations of this project was the relatively low participation rate. There were several contributors to this issue that could be avoided by future efforts. First, the current project was an isolated study rather than part of a larger effort. It is likely that situating DR event requests in the context of a broader, more well-known program, would garner more support and participation. Future efforts should either leverage existing broader-scale programs, or create new ones, either of which could incorporate DR events as one element. An alternate idea involves creating a champion system, whereby “energy champions” are recruited from among participants, and then asked to promote the program within their departments or offices. This method is likely to be effective if the champions are trusted, or at least familiar, to their constituents. Finally, hierarchical recruitment, physical recruitment materials, and program kick-off workshops or meeting should also be considered, depending on the context.
- Ensure Perception of Message Authenticity
    - Caution should be exercised in constructing recruitment messages. This project was unique in that messaging sources were manipulated, so in both anthropomorphism conditions, messages were framed as coming from participants’ office buildings. Several participants contacted the study team concerned that messages were “phishing” or internet “spam”. Efforts to confirm study authenticity, and university support, are therefore critical. Strategies may include: contacting University IT systems and Deans, using official institutional letterhead, and including on materials links to trusted web pages and names and contact information for study personnel. The present study employed all of the above strategies except for investigator names and contact information.

This information was purposely excluded due to the nature of the experiment testing for source effects. Including names would have negatively impacted the internal validity of the experiment. Additional strategies include sending messages form well-known institutional administrators accounts, or building up trust in the program prior to requesting participation in DR events (see preceding "Lessons Learned" bullet point). Related to "spam" suspicions, several participants contacted study staff to complain about doubtful legitimacy of messages. Each complaint was addressed on a one-on-one basis, and complainants were generally placated after being reassured the messages were not spam.

- Be clear with requests
    - Some participants contacted study personnel to convey that they could not participate because they did not have control over their thermostats, demonstrating some level of misunderstanding over the request that was made. It is possible that requesting participation in very specific behaviors (e.g., unplug large office equipment) would enhance compliance because it would reduce ambiguity about what is being asked, eliminate the need for participants to think about what actions they might execute, and instead presents the request as a simple, straightforward action.
- Protect workplace productivity
    - The present study focused on employees in office buildings. Therefore, it was important to emphasize to administrators and participants alike that participation should not negatively impact workplace productivity.
- Allocate sufficient resources
    - To enhance participation levels, adequate study resources and staffing are required. The present project would have benefited from additional staff effort on recruitment. Planning up front for these resources is critical to successful project execution.

8. Summary of future plans and next steps with respect to additional testing, demonstration, or deployment

During Operations, persuasive messages to promote participation in DR events will be deployed at the USC microgrid and among LADWP residential and commercial customers. The lessons learned from the present project have directly informed our DR messaging plans for Operations. For instance, allotting adequate time and resources towards recruitment will be a key thrust. Additionally, messaging will test the concept of specific behavioral requests. For instance, we will examine the impact of messages that ask participants

to adjust their thermostats by a few degrees relative to messages that simply ask participants to conserve energy.

Appendix A: Messages

MESSAGE 1

SUBJECT: USC campus Save Power Event program

Hello Trojan,

As part of the Living Laboratory collaboration here at USC, we invite you to participate in the Save Power Event Program with your colleagues across USC's campus. This Program is part of a research study--your email address was provided to us by USC administration. Participation is voluntary.

During the Save Power Event, you will be asked to conserve power in your work station for a few hours by choosing one or more power-saving actions, such as adjusting thermostats, turning off unnecessary lights, reducing machine usage, or heating and air conditioning. Please join your colleagues in this effort to prevent power outages and reduce energy waste in your building.

You will be notified by email two days before a Save Power Event, and alerted again one hour prior to the Event, so please be on the lookout for emails from us.

We've provided some examples of behaviors that you can take during a Save Power Event:

- Use e-copies instead of printing
- Turn off machines not in use
- Keep doors closed if it helps temperature regulation
- Wait to use office equipment (e.g. printers, copies, scanners)
- Manage temperature and lighting with windows and shades
- Turn off or unplug machines not in use
- Set your devices to Energy saver mode

- Regulate the thermostat (68 degrees when it is cold, 78 degrees when it is hot)
- Keep exterior doors and windows closed to conserve heat (when cold outside) and cooling (when it is hot outside).

You will also be asked to completed brief surveys about the Save Power Events. You will be receiving more emails in the future.

If you would like more information about the program, please visit the website at http://losangeles.usc.edu, or feel free to email spe-team@usc.edu.

MESSAGE 2

1st person anthro

SUBJECT: USC campus Save Power Event on XX day

Hello again Trojan,

I am your building; I wanted to let you know that the campus wide Save Power Event

will be occurring two days from now, XX day, from XXam-XXpm.

While participation is voluntary, I have provided some additional information about why this program is important:

Did you know that we buildings have a lot in common with human beings? We have

separate parts, just like organs that work dynamically together to create a product. We also have desires and needs. Similar to humans, we know when we need more energy to function effectively. Just like when you get overworked or are low on energy, you feel tired and don't perform at your best, I also can feel fatigue. It's important to be aware that just like you, we buildings have limits. We can get tired and worn out. When we buildings are overworked, we cannot provide you with the necessities that you need to be productive. Scheduled breaks sometimes prevent power outages, so it's in everyone's interest to allow us buildings time off.

Please join the Save Power Event Program and reduce your energy consumption in order to give me time to rest and recover.

You will be hearing from me again when the Save Power Event is one hour away from occurring, on XX day at XXam.

If you would like more information about the program, please visit the website at http://losangeles.usc.edu, or feel free to email spe-team@usc.edu.

3rd person anthro

SUBJECT: USC campus Save Power Event on XX day

Hello again Trojan,

Your building wanted to let you know that the campus wide Save Power Event will be occurring two days from now, XX day, from XXam-XXpm.

While participation is voluntary, your building has provided some additional information about why this program is important:

Did you know that buildings have a lot in common with human beings? They have separate parts, just like organs that work dynamically together to create a product. They also have desires and needs. Similar to humans, they know when they need more energy to function effectively. Just like when you get overworked or are low on energy, you feel tired and don't perform at your best, buildings also can feel fatigue. It's important to be aware that just like us, buildings have limits. They can get tired and worn out. When buildings are overworked they cannot provide you with the necessities that you need to be productive. Scheduled breaks sometimes prevent power outages, so it's in everyone's interest to allow us buildings time off.

Please join the Save Power Event Program and reduce your energy consumption in order to give your building time to rest and recover.

You will be hearing from your building again when the Save Power Event is one hour away from occurring, on XX day at XXam.

If you would like more information about the program, please visit the website at http://losangeles.usc.edu, or feel free to email spe-team@usc.edu.

Control

SUBJECT: USC campus Save Power Event on XX day

Hello again Trojan,

This is to let you know that the campus wide Save Power Event will be occurring two days from now, XX day, from XXam-XXpm.

While participation is voluntary, this is some additional information about why this program is important:

How much do you know about buildings? They have separate parts that work like a machine dynamically together to create a product. Buildings also need fuel in order to function effectively. When buildings get overused or when energy is not available, they don't execute functions optimally. It's important to be aware that buildings have limits. When buildings are used too heavily they cannot provide you with the necessities that you need to be productive. Scheduled breaks sometimes prevent power outages, so it's in everyone's interest to decrease demand on the building.

Please join the Save Power Event Program and reduce your energy consumption in order for your building to reboot.

You will be emailed again when the Save Power Event is one hour away from occurring, on XX day at XXam.

If you would like more information about the program, please visit the website at http://losangeles.usc.edu, or feel free to email spe-team@usc.edu.

MESSAGE 3

1st person antho

SUBJECT: USC campus Save Power Event today @ XX am-XX pm

Hello Trojan,

This is your building; I wanted to let you know that the USC campus-wide Save Power Event will be starting in the next hour. The event will last from XXam-XXpm today, and participation is voluntary.

I have provided a reminder of the Save Power Event Program and also some helpful suggestions to aid you in your energy conservation.

During the Save Power Event, I am asking you to voluntarily conserve power in your work stations for a few hours by choosing one or more power-saving actions for me, such as adjusting thermostats, using fewer lights, reducing machine usage, heat, and air conditioning. Please join your colleagues in this effort to prevent power outages and reduce energy waste in me, your building. Here are some suggestions for actions you may choose to take during the Save Power Event today:

- Use e-copies instead of printing
- Turn off machines not in use
- Keep doors closed if it helps temperature regulation
- Wait to use office equipment (e.g. printers, copies, scanners)
- Manage temperature and lighting with windows and shades
- Turn off or unplug machines not in use
- Set your devices to Energy saver mode
- Regulate the thermostat (68 degrees when it is cold, 78 degrees when it is hot)
- Keep exterior doors and windows closed to conserve heat (when cold outside) and cooling (when it is hot outside).

As your building, I really appreciate you taking the time to conserve energy and to give me a well-deserved rest. Thank you!

If you would like more information about the program, please visit the website at http://losangeles.usc.edu, or feel free to email spe-team@usc.edu.

3rd person anthro

SUBJECT: USC campus Save Power Event today @ XX am-XX pm

Hello Trojan,

Your building wanted to let you know that USC campus-wide Save Power Event will be starting in the next hour. The event will last from XXam-XXpm today, and participation is voluntary.

Your building has provided a reminder of the Save Power Event Program and also some helpful

suggestions to aid you in your energy conservation.

During the Save Power Event, your building is asking you to voluntarily conserve power in your work stations for a few hours by choosing one or more power-saving actions for your building, such as adjusting thermostats, using fewer lights, reducing machine usage, heat, and air conditioning. Please join your colleagues in this effort to prevent power outages and reduce energy waste in your building. Here are some suggestions for actions you may choose to take during the Save Power Event today:

- Use e-copies instead of printing
- Turn off machines not in use
- Keep doors closed if it helps temperature regulation
- Wait to use office equipment (e.g. printers, copies, scanners)
- Manage temperature and lighting with windows and shades
- Turn off or unplug machines not in use
- Set your devices to Energy saver mode

• Regulate the thermostat (68 degrees when it is cold, 78 degrees when it is hot)

• Keep exterior doors and windows closed to conserve heat (when cold outside) and cooling (when it is hot outside).

Your building appreciates you taking the time to conserve energy and to give it a well-deserved rest. On behalf of your building, thank you!

If you would like more information about the program, please visit the website at http://losangeles.usc.edu, or feel free to email spe-team@usc.edu.

Control

SUBJECT: USC campus Save Power Event today @ XX am-XX pm

Hello Trojan,

This is to let you know that the USC campus-wide Save Power Event will be starting in the next hour. The event will last from XXam-XXpm today, and participation is voluntary.

This is a reminder of the Save Power Event Program and some helpful suggestions to aid you in your energy conservation.

During the Save Power Event, you are being asked to voluntarily conserve power in your work stations for a few hours by choosing one or more power-saving actions, such as adjusting thermostats, using fewer lights, reducing machine usage, heat, and air conditioning. Please join your colleagues in this effort to prevent power outages and reduce energy waste.

Here are some suggestions for actions you may choose to take during the Save Power Event

today:

• Use e-copies instead of printing

• Turn off machines not in use

• Keep doors closed if it helps temperature regulation

• Wait to use office equipment (e.g. printers, copies, scanners)

• Manage temperature and lighting with windows and shades

• Turn off or unplug machines not in use

• Set your devices to Energy saver mode

• Regulate the thermostat (68 degrees when it is cold, 78 degrees when it is hot)

• Keep exterior doors and windows closed to conserve heat (when cold outside) and

cooling (when it is hot outside).

It is appreciated that you are taking the time to conserve energy and reduce demand. Thank you!

If you would like more information about the program, please visit the website at http://losangeles.usc.edu, or feel free to email spe-team@usc.edu.

MESSAGE 4 (JUNE 27, 2013 VERSION)

SUBJECT: Help USC and Enter for a Chance to Win a $500 Gift card--Save Power Event Opinion Survey

Hello Trojan,

Now that the Save Power Event is over, your feedback is requested. Please click the link below to begin the brief survey. You may stop taking the survey at any point and your responses will remain confidential. Participants who complete the survey will be entered into a raffle to win a $500 Visa gift card. At the end of the survey you will need to provide an email so that we can

contact you if you win.

Your feedback is critical in helping USC design future Save Power Events and in helping the environment more generally.

Click here to take the survey or copy and paste it in your internet browser:

https://usccollege.qualtrics.com/SE/?SID=SV_5cgHS5QdoqQ0vl3

Participation is voluntary and will not affect your relationship with USC.

There will be future Save Power Events, so be on the lookout for more emails. Thank you.

If you would like more information about the program, please visit the website at http://losangeles.usc.edu, or feel free to email spe-team@usc.edu.

Appendix B: Post-DR event Survey

consent University of Southern California INFORMATION SHEET FOR NON-MEDICAL RESEARCH "Save Power Events Project" PURPOSE OF THE STUDY You are invited to participate in a research study conducted by the Lead of the Decision Systems group, Michael D. Orosz, Ph.D. and Smart Grid Customer Behavior Project Lead Nicole D. Sintov, Ph.D., both of the USC Information Sciences Institute. The study is funded by the United States Department of Energy and the Los Angeles Department of Water and Power (LADWP). Energy systems throughout the country are being updated as technology improves. USC is exploring ways to use emerging technologies to better monitor and supply

power to all buildings on and around campus in increasingly energy-efficient ways. We are interested in learning about your opinions regarding energy use and conservation, and preferences related to energy management services in your workplace that may be offered in the future. ELIGIBILITY To participate in this study, you must be at least 18 years of age and a part-time or full-time employee of the University of Southern California's University Park Campus, including student workers. Participating in this study is voluntary. You may terminate your participation at any time. Please read the information below before deciding whether or not to participate. STUDY TASKS If you agree to participate in this study, you will be asked to complete questions about your Save Power Event experience and answer questions about yourself. You may be asked to complete up to five surveys in 2013. Each survey is anticipated to take no more than 5 minutes to complete. COMPENSATION FOR PARTICIPATION For responding to this survey, you will receive one entry into a raffle to win a $500 Visa Gift Card. You will have the opportunity to complete the same survey in the future. For each new survey you respond to, you will receive an additional entry into the raffle. CONFIDENTIALITY Your participation is confidential. The data will be stored as coded to protect your confidentiality and stored on a password-protected computer. Identifiable information will be destroyed upon completion of the study; the de-identified data will be retained indefinitely and may be used in future research studies. If you do not want the data to be used in future studies, you cannot participate in this study. The members of the project team at USC, University of California at Los Angeles (UCLA), and at Los Angeles Department of Water and Power, as well as the University of Southern California's Human Subjects Protection Program (HSPP) may access the data. The HSPP reviews and monitors research studies to protect the rights and welfare of research subjects. When the results of the research are published or discussed in conferences, no identifiable information will be used. PARTICIPATION AND WITHDRAWAL Your participation is voluntary. Your refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You may withdraw your consent at any time and discontinue participation without penalty. If you withdraw participation, you will no longer be able to access the energy management tools provided exclusively to participants in this study. You are not waiving any legal claims, rights, or remedies because of your participation in this research project. ALTERNATIVES TO PARTICIPATION Your alternative is to not participate in this study. Your status as a student, staff or faculty will not be affected, whether or not you participate in this study. IDENTIFICATION OF INVESTIGATORS If you have any questions or concerns related to this research, you may contact: Nicole D. Sintov, Ph.D. Behavioral Scientist Los Angeles Regional Smart Grid Demonstration Project Information Sciences Institute Viterbi School of Engineering University of Southern California 4676 Admiralty Way, Suite 1001 Marina del Rey, CA 90292 Tel 310.448.9182 nisintov@isi.edu If you have any questions about your rights as a study subject or you would like to speak with someone independent of the research team to have questions answered about this project, or in the event the research staff cannot be reached, please contact the University Park Institutional Review Board (UPIRB), 3720 South Flower Street #301, Los Angeles, CA 90089- 0702, (213) 821-5272 or upirb@usc.edu

intro Thank you for agreeing to fill out this 3-4 minute survey following the May 1st, 2013 Save Power Event on USC's University Park Campus. We mentioned in previous emails that we would want your input on the event. For completing this survey, you will receive one raffle entry to win a $500 Visa giftcard. We ask that as you go through the survey, and answer honestly. There are no wrong or right answers. Towards the end of survey, separate from your other responses, you will be prompted to enter your email so that we can contact you should you win the raffle. Once again, thank you for taking the time to complete this short survey.

EmployUSC Are you currently faculty or staff at USC?

- Yes (1)
- No (2)

code Please provide your date of birth along with your first and last initials. We remind you that your responses are confidential. This means we do not know who is filling out these surveys. This creates a conflict, as we will be sending future surveys. Therefore, we need to be able to link the surveys with a special code. The special code is created by combining your date of birth with your initials. We respect your privacy, and the responses you provide will only be accessible to the study team.

Please provide your birthday (MMDDYY). For example, May 25, 1970 = 052570. (1)

Please provide your first and last initials. For example, John Smith = JS. (2)

building Do you currently work in a building at the University of Southern California?

- Yes (1)
- No (2)

Answer If Yes Is Selected

addAbrevs Which of the following campus buildings do you work in?(Please click the dropdown menu to choose your building).

- 3434 S. GRAND BUILDING / URBNMRKT (CAL) (1)
- ACCOUNTING LIBRARY (ACC) (2)

- ALLAN HANCOCK FOUNDATION BUILDING (AHF) (3)
- ANDRUS GERONTOLOGY CENTER (GER) (4)
- ANNENBERG SCHOOL FOR COMMUNICATION (ASC) (5)
- AT&T BUILDING (ATT) (6)
- BIEGLER HALL OF ENGINEERING (BHE) (7)
- BING AUDITORIUM (BIT) (8)
- BOVARD ADMINISTRATION BUILDNG (ADM) (9)
- BRIDGE MEMORIAL HALL (BRI) (10)
- CHILDS WAY BUILDING II (CWT) (11)
- DENNEY RESEARCH CENTER (DRB) (12)
- DOHENY MEMORIAL LIBRARY (DML) (13)
- DRAMA CENTER (DRC) (14)
- GRACE FORD SALVATORI HALL OF LETTERS, ARTS & SCIENCES (GFS) (15)
- GWYNN WILSON STUDENT UNION (STU) (16)
- HARRIS HALL, QUINN WING & FISHER GALLERY (HAR) (17)
- HAZEL & STANLEY HALL FINANCIAL SERVICES BUILDING (HSH) (18)
- HEDCO NEUROSCIENCES BUILDING (HNB) (19)
- HOFFMAN HALL OF BUSINESS ADMINISTRATION (HOH) (20)
- HUBBARD HALL (JHH) (21)
- HUGHES AIRCRAFT ELECTRICAL ENGINEERING CENTER (EEB) (22)
- JANE HOFFMAN POPOVICH & J. KRISTOFFER POPOVICH HALL (JKP) (23)
- KAPRIELIAN HALL (KAP) (24)
- LEAVEY LIBRARY (LVL) (25)
- LYON UNIVERSITY CENTER (LRC) (26)
- MCCLINTOCK BUILDING AND THEATRE (MCC) (27)

- MONTGOMERY ROSS FISHER BUILDING SCHOOL OF SOCIAL WORK (MRF) (28)
- MUDD MEMORIAL HALL OF PHILOSOPHY (MHP) (29)
- MUSICK LAW BUILDING CENTER (LAW) (30)
- NORRIS DENTISTRY BUILDING (DEN) (31)
- OLIN HALL OF ENGINEERING (OHE) (32)
- PERTUSATI UNIVERSITY BOOKSTORE (BKS) (33)
- PHYSICAL EDUCATION BUILDING (PED) (34)
- RALPH AND GOLDY LEWIS HALL (RGL) (35)
- SALVATORI COMPUTER SCIENCE CENTER (SAL) (36)
- SCENE DOCK THEATRE (SCD) (37)
- SEELEY G. MUDD BUILDING (SGM) (38)
- SOCIAL SCIENCES BUILDING (SOS) (39)
- SOCIAL WORK CENTER (SWC) (40)
- STAUFFER HALL (SHS) (41)
- STAUFFER SCIENCE LECTURE HALL (SLH) (42)
- STONIER HALL (STO) (43)
- TAPER HALL OF HUMANITIES (THH) (44)
- TUTOR CAMPUS CENTER (TCC) (45)
- TUTOR HALL (RTH) (46)
- UNITED UNIVERSITY CHURCH (UUC) (47)
- UNIVERSITY GATEWAY (UGW) (48)
- VON KLEINSMID CENTER (VKC) (49)
- WAITE PHILLIPS HALL OF EDUCATION (WPH) (50)
- WATT HALL OF ARCHITECTURE & FINE ARTS (WAH) (51)
- WIDNEY ALUMNI HOUSE (ALM) (52)

- ZUMBERGE HALL (ZHS) (53)
- OTHER (54)

Answer If Which of the following campus buildings do you work in?(P... OTHER Is Selected

otherBuild If you indicated "Other" above, please type out your building and it's building code if you know that as well.

participat Did you participate in the Save Power Event on Wednesday May 1, 2013? By participation we mean taking active steps to reduce energy consumption.

- Yes (1)
- No (2)

Answer If Did you participate in the Save Power Event on [date]?&nb... Yes Is Selected

HowLngPart For how long did you participate?

- Fewer than 10 minutes (1)
- About 10 minutes (2)
- About 20 minutes (3)
- A half hour (4)
- About an hour (5)
- About 1.5 hours (6)
- About 2 hours (7)
- About 3 hours (8)
- About 4 hours (9)
- More than 5 hours (10)

Answer If Did you participate in the Save Power Event on [date]? No Is Selected

whynop Why didn't you participate? (Choose all that apply)

- ☐ I didn't know it was happening (1)
- ☐ I received the notification too late and couldn't take the appropriate actions (2)
- ☐ Others in my workstation needed me to maintain my equipment. (3)
- ☐ I was distracted and wasn't able to take action. (4)
- ☐ I thought my productivity would be negatively impacted. (5)
- ☐ I didn't want to be uncomfortable (6)
- ☐ It might have been inconvenient to participate (7)
- ☐ I wasn't sure what actions to take (8)
- ☐ I didn't think any actions I could take would have made a contribution (9)
- ☐ It was not important to me to participate (10)
- ☐ Other (please specify) (11) _____

If I didn't know it was happening Is Displayed, Then Skip To Did you know whether other colleagues...

hvac1 Which of the following do you have in your personal workstation?

- ☐ Thermostat that controls heating and cooling (1)
- ☐ Wall or window air conditions unit (2)
- ☐ Electric Space heater (5)
- ☐ Computer (6)
- ☐ Printer (7)
- ☐ Power strip (8)
- ☐ Microwave (9)
- ☐ Mini refrigerator (10)
- ☐ Desk or upright oscillating fan (11)

- fax machine (12)
- lab equipment (e.g. centrifuge) (13)
- Full size refrigerator (14)

Answer If Which of the following do you have in your personal works... QID11 (Count) Is Greater Than 0

HvacCntrl Of the equipment you selected, which do you have direct control over (i.e. you can adjust the settings as you wish)?

- Thermostat that controls heating and cooling (1)
- Wall or window air conditions unit (2)
- Electric Space heater (5)
- Computer (6)
- Printer (7)
- Power strip (8)
- Microwave (9)
- Mini refrigerator (10)
- Desk or upright oscillating fan (11)
- fax machine (12)
- lab equipment (e.g. centrifuge) (13)

Answer If Which of the following do you have in your personal works... QID11 (Count) Is Greater Than 0

Q87 Of the equipment you selected, which could you potentially control but do not feel at liberty to alter? (For example, if you were in a shared space and it was not clear who had control over certain systems, you might not feel at liberty to alter them.)

- Thermostat that controls heating and cooling (1)
- Wall or window air conditions unit (2)

- Electric Space heater (5)
- Computer (6)
- Printer (7)
- Power strip (8)
- Microwave (9)
- Mini refrigerator (10)
- Desk or upright oscillating fan (11)
- fax machine (12)
- lab equipment (e.g. centrifuge) (13)

Answer If Which of the following do you have in your personal works... Thermostat that controls heating and cooling Is Selected

hvac2 What adjustments, if any, did you make to your work station's thermostat during the Save Power Event with the intention of saving energy?

Degrees Fahrenheit (1)

Before the event, my thermostat was set to (1)

During the event, I adjusted it to (2)

Answer If Which of the following do you have in your personal works... Wall or window air conditions unit Is Selected

hvac3 What adjustments, if any, did you make to your air conditioning unit during the Event with the intention of saving energy?

Low (1) Medium (2) High (3) Off (4) Other (5)

Before the event, my air conditioning unit was set to (1)

During the event, I adjusted it to (2)

Answer If Which of the following do you have in your personal works... Electric Space heater Is Selected

Q15 What adjustments, if any, did you make to your electric space heater during the Event with the intention of saving energy?

Low (1) Medium (2) High (3) Off (4)

Before the event, my electric space heater was set to (1)

During the event, I adjusted it to (2)

PrcvdCntrl How much control would you say that you have over your own energy use within your workstation?

- 1-No control (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)
- 6 (6)
- 7-Total Control (7)

Answer If Did you participate in the Save Power Event on [date]? Yes Is Selected

axns What other actions did you take during the Event with the intention of saving energy? Please select all that apply.

- Put on an additional layer of clothing (1)

- Removed a layer of clothing (2)
- Got a hot beverage (3)
- Got cold beverage (4)
- Adjusted window shades to block sun (5)
- Adjusted window shades to allow sun in (6)
- Turned off lights that were not in use (7)
- Turned off office devices (e.g. copy machine) (8)
- Turned off lab equipment (9)
- Encouraged others in my office to participate (10)
- Unplugged devices (e.g. computers) (11)
- Left my office (12)
- Other (please specify) (13) _____
- Opened window (14)
- Closed window (15)
- Adjusted thermostat (16)
- Put devices in "sleep mode" (17)

SubjPartic To what extent did you participate in the Save Power Event?If you had to estimate your effort or involvement, what would you say?

- 1-Not at all (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)
- 6 (6)

- 7-Very much (7)

comfor Rate your level of physical comfort during the Event.

- Very uncomfortable (1)
- Slightly uncomfortable (2)
- Neutral (3)
- Slightly comfortable (4)
- Very comfortable (5)

futur How likely are you to participate in a future Save Power Event?

- Very Unlikely (1)
- Unlikely (2)
- Somewhat Unlikely (3)
- Undecided (4)
- Somewhat Likely (5)
- Likely (6)
- Very Likely (7)

Answer If Did you participate in the Save Power Event on [date]? Yes Is Selected

whyp We're interested in knowing what might have influenced you to participate in today's event. Why did you participate? (select all that apply)

- Other people I know were participating. (1)
- I thought it was mandatory. (2)
- I thought it was important to do for the building (3)
- I feel strongly about energy conservation. (4)

 Other (please specify) (5) _____

OthersPart Did you know whether other colleagues in your building would be participating in the Save Power Event?

 Yes (1)

 No (2)

Answer If Yes Is Selected

howManyOth You indicated that others in your building would be participating. What percentage would you say were prepared to participate?

_____ % of people prepared to participate (1)

inst Thank you for your responses. For the next questions, we're interested in how you feel about the following things you might encounter in your day:

ConctNat1 I often feel a strong connection to nature.

 Strongly Disagree (1)

 Disagree (2)

 Neither Agree nor Disagree (3)

 Agree (4)

 Strongly Agree (5)

ConctNat2 I feel that all living things in this world are connected, and I am a part of that.

 Strongly Disagree (1)

 Disagree (2)

 Neither Agree nor Disagree (3)

- Agree (4)
- Strongly Agree (5)

anthroInst Below, we will ask you to rate the extent to which you believe various items possess certain capacities. On a 0-10 scale (where 0 = “Not at All” and 10 = “Very much”), please rate the extent to which the item possesses the capacity given. Please click a number to indicate your response.

CompActiv To what extent is the average computer active? (By “active” we mean moving frequently and quickly.)

- 0-Not at all (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10-Very much (11)

techIntent To what extent do technological devices have intentions?(By “has intentions” we mean has preferences and plans.)

- 0-Not at all (1)
- 1 (2)
- 2 (3)

- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10-Very much (11)

BuildConsc To what extent does the average building have consciousness. (By “has consciousness” we mean able to be aware of itself and its thoughts and feelings.)

- 0-Not at all (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10-Very much (11)

LtSwtEmot To what extent does a light switch experience emotions?(By “can experience emotion” we mean it has feelings.)

- 0-Not at all (1)

- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10-Very much (11)

inst As part of this program, we are considering different types of message appeals and would appreciate your feedback on the following questions.

source Before the Save Power Event, you received emails from the "Save Power Event Team" (spe-team@usc.edu) explaining what a Save Power Event was and indicating when it would occur. We'd like you to indicate (if you remember) within the body of the email, from whom or from what perspective was the information provided?

- Building manager (1)
- The Building (2)
- President of the University (3)
- Provost of Research (4)
- Another USC staff member (5)
- Don't recall (6)

NEWManpChk Before the Save Power Event, you received emails indicating the impending Save Power Event. Which of the following statements did you see in the email that was sent out? (Your responses won't affect your raffle entry, we are just interested in what you recall).

- Did you know that we buildings have a lot in common with human beings? We have separate parts, just like organs that work dynamically together to create a product. (1)
- Did you know that buildings have a lot in common with human beings? They have separate parts, just like organs that work dynamically together to create a product. (2)
- How much do you know about buildings? They have separate parts that work like a machine dynamically together to create a product. (3)

inst Thank you, you are nearly finished. Please tell us a bit about you. Please remember your responses are confidential.

Wrk+1yr? Have you worked for a year or more at the University of Southern California?

- Yes (1)
- No (2)

Answer If Have you worked for a year or more at the University of S... Yes Is Selected

TenureUniv How long have you worked for the University?

- 1 year (1)
- 2 years (2)
- 3 years (3)
- 4 years (4)
- 5 years (5)
- 6 years (6)
- 7 years (7)
- 8 years (8)

- 9 years (9)
- 10 years (10)
- 11 years (11)
- 12 years (12)
- 13 years (13)
- 14 years (14)
- 15 years (15)
- 16 years (16)
- 17 years (17)
- 18 years (18)
- 19 years (19)
- 20 years (20)
- 21 years (21)
- 22 years (22)
- 23 years (23)
- 24 years (24)
- 25 years (25)
- more than 25 years (26)

Answer If Have you worked for a year or more at the University of S... Yes Is Selected

BuildYrs How many years have you worked in the building that you work in now?

- 1 year (1)
- 2 years (2)
- 3 years (3)
- 4 years (4)

- 5 years (5)
- 6 years (6)
- 7 years (7)
- 8 years (8)
- 9 years (9)
- 10 years (10)
- 11 years (11)
- 12 years (12)
- 13 years (13)
- 14 years (14)
- 15 years (15)
- 16 years (16)
- 17 years (17)
- 18 years (18)
- 19 years (19)
- 20 years (20)
- 21 years (21)
- 22 years (22)
- 23 years (23)
- 24 years (24)
- 25 years (25)
- more than 25 years (26)

Answer If Have you worked for a year or more at the University of S... No Is Selected

MnthsTenur How many months have you worked at USC?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10 (11)
- 11 (12)

Answer If Have you worked for a year or more at the University of S... No Is Selected

BuildMnths How many months have you worked in the building you work in now?

- 1 (1)
- 2 (2)
- 4 (3)
- 3 (4)
- 5 (5)
- 6 (6)
- 7 (7)
- 8 (8)
- 9 (9)
- 10 (10)

- 11 (11)

hrsOffice In order to better understand your energy usage, could you please provide a response to the following: On average, how many hours do you spend in your office daily?

- less than 1 hour (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10 or more hours (11)

gender Please indicate your gender.

- Male (1)
- Female (2)
- Prefer not to respond (3)

age Please indicate your age:(Click on the dropdown menu below).

- 18 (1)
- 19 (2)
- 20 (3)

- 21 (4)
- 22 (5)
- 23 (6)
- 24 (7)
- 25 (8)
- 26 (9)
- 27 (10)
- 28 (11)
- 29 (12)
- 30 (13)
- 31 (14)
- 32 (15)
- 33 (16)
- 34 (17)
- 35 (18)
- 36 (19)
- 37 (20)
- 38 (21)
- 39 (22)
- 40 (23)
- 41 (24)
- 42 (25)
- 43 (26)
- 44 (27)
- 45 (28)

- 46 (29)
- 47 (30)
- 48 (31)
- 49 (32)
- 50 (33)
- 51 (34)
- 52 (35)
- 53 (36)
- 54 (37)
- 55 (38)
- 56 (39)
- 57 (40)
- 58 (41)
- 59 (42)
- 60 (43)
- 61 (44)
- 62 (45)
- 63 (46)
- 64 (47)
- 65 (48)
- 66 (49)
- 67 (50)
- 68 (51)
- 69 (52)
- 70 (53)

- 71 (54)
- 72 (55)
- 73 (56)
- 74 (57)
- 75 (58)
- 76 (59)
- 77 (60)
- 78 (61)
- 79 (62)
- 80 (63)

political Please indicate your political orientation:(Move the slider in the middle closest to your desired sentiments).

_____ - (1)

inst You are now done with the majority of the survey. If you'd like to answer just two more optional questions, please do so below. If not, please click the "Next" button to go to the next page where you can enter your contact information to be included in the raffle.

effective How effective do you think your individual actions were for energy conservation efforts?

- Very Ineffective (1)
- Ineffective (2)
- Somewhat Ineffective (3)
- Neither Effective nor Ineffective (4)
- Somewhat Effective (5)
- Effective (6)

- Very Effective (7)

effort How much effort do you think you expended throughout the Save Power Event in order to save energy?

- 1-None at all (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5- A lot (5)

lastStep You have completed all of the questions. Please continue so that you can enter your contact information for the $500 raffle. We separate your contact information from your survey responses to protect your identity. Please continue to the final step.

raffle Please enter your USC email address below to earn one entry into the raffle drawing for a $500 Visa gift card. Note that we cannot include non-USC email addresses in the raffle so be sure to enter your University email address. Be sure to click the "next" button to make sure your email address is recorded.

Acknowledgements

We thank Dr. Adam Waytz for his valuable input on the design of the experimental messages.

Appendix L Summary Report USC Campus Microgrid Experiment: Energy Usage Reduction Competition Among Dormitory Residents

Summary Report

USC Campus Microgrid Experiment:

Energy Usage Reduction Competition Among Dormitory Residents

Los Angeles Department of Water and Power Smart Grid Regional Demonstration Program

Customer Behavior Project

January 30, 2015

This material is based upon work supported by the Department of Energy under Award Number DE-OE0000192 and funding from the Los Angeles Department of Water and Power.

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1. Change History

e. Author(s): Ellen Dux, Nicole Sintov
f. Reviewer/Approvers: Justin Powels

2. Executive Summary

Structured as a building-wide energy reduction competition for freshmen residents of Fluor Tower on the University of Southern California campus, our experiment examined the effectiveness of a competition leveraging energy use feedback enabled by "smart meters" and an interactive energy kiosk as a framework for reducing energy consumption among university dormitory occupants. The "Fluor Tower, Flex Your Power!" demonstration was designed to determine residents' attitudes towards energy consumption, and formulate and analyze strategies for encouraging energy conservation. Our study sought to understand what goes on "behind the electric meter" during an energy efficiency intervention. We found that promoting energy behavior awareness enhanced by "smart grid" technology-enabled usage feedback; normative behavior cues, rewards, and information about how to effect change prompts behavioral changes that can result in increased energy efficiency and load shed reductions.

We instrumented the residential suites in Fluor Tower with digital "smart" electric meters, which recorded the occupants' energy consumption in 15-minute intervals. Suite-level energy feedback was pass-coded for anonymity and security, and made available to residents via an interactive touch-screen kiosk located in the building lobby. The kiosk was leveraged as part of a three-week competition period during which suites competed against one another to reduce their energy consumption to win prizes. Suites' rankings in the competition were updated continuously at the kiosk, and residents were also informed of their standings via flyers and emails. Participants also completed baseline and follow-up surveys that assessed self-efficacy beliefs; self-reported conservation and peak demand reduction behaviors; and intentions to participate in future campus energy efficiency measures. The competition also included two voluntary curtailment demand response (DR) events.

Approximately 22% of Fluor Tower residents formally participated in the competition as assessed via survey response rate. Cumulatively, residents saved 3,158 kWh of electricity in three weeks, the equivalent of 3473 pounds of avoided carbon dioxide emissions. This reduction occurred although the intervention took place during a period of very high temperatures and all-time record high electricity demand in Los Angeles.

As the outcome to this experiment, we hypothesized that we would observe a decrease in suite-level energy consumption during the intervention relative to the baseline period, after controlling for factors known to influence energy consumption such as outdoor temperature. We also hypothesized that a further decrease in

energy use would be observed during the two demand response/load curtailment events, relative to non-DR periods.

In conclusion, prompting energy behavior awareness via an energy competition intervention that is enabled by feedback from technologies such as smart meters and energy kiosks, normative behavior cues, rewards, and information results in behavioral changes that can cause reductions in energy consumption. Understanding how intervention strategies spur and sustain behavior change will enable the development of more streamlined and targeted interventions. Such knowledge can then be used to shape strategies for future energy conservation programs at the utility level. The knowledge gained from this research project contributes to the overall understanding of personal energy usage reduction as demonstrated by campus energy competitions.

3. An Overview of the Demonstration

At a high level, one goal of the LADWP Smart Grid Regional Demonstration Program (SGRDP) is to collect and provide the optimal amount of information necessary for customers to change their behavior in a way that reduces system demands and costs; increases energy efficiency; optimizes the allocation and match of demand and resources; and increases grid reliability.

For the Customer Behavior (CB) project portion of SGRDP, a comprehensive portfolio of customer behavioral studies are being conducted to demonstrate the impact of smart grid communication systems and processes on customer usage patterns, as well as energy savings resulting from the use of smart grid enabled interfaces. Our CB experiment demonstrates this by showing how innovations in smart grid technologies can be combined with empirically validated social science approaches to develop effective new energy management strategies.

Our research shows that promoting energy behavior awareness enhanced by smart grid technology-enabled usage feedback; normative behavior cues, rewards, and information about how to effect change prompts behavioral changes that can result in increased energy efficiency and load shed reductions. With the availability of high-resolution data visualization on real-time energy use, utilities can now help consumers associate personal energy behaviors with energy consumption and cost.

a. Smart Grid capabilities and functions demonstrated

The study demonstrated the following functions from the SGRDP's Statement Of Program Objectives (SOPO):

- Demonstrate the impact of Smart Grid communication systems and processes on customer usage patterns
- Demonstrate effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns
- Demonstrate consumer outreach and messaging strategies on Smart Grid deployment, incorporating changes observed in awareness, attitudes, and energy use behaviors

b. Smart Grid impacts and benefits demonstrated

Planned impacts and benefits from this demonstration include the following:

- Determine the influence of the availability of real-time energy usage data on energy behavior
- Identify load shed possible via energy curtailment in a dormitory building
- Evaluate how energy behavior awareness - enhanced by timely usage feedback,

- normative behavior cues, rewards, and information about how to affect change - prompts behavioral changes that can result in energy usage changes

- Provide insights into the potential mediating roles of self-efficacy, group identification, and the relationship between behavioral feedback and behavior change, as applied to energy management behaviors

- Use information to inform strategies for energy management programs at the utility level

c. List of objectives/scope

The Fluor Tower energy competition demonstration will simulate customer engagement and interaction, which will help inform and guide Customer Behavior studies at the utility level.

d. Mapping to the SOPO and deliverables

The following deliverables from the SOPO are presented in this report:

- Identification of the effective individual and group participation mechanisms for increasing energy awareness and improving usage patterns
- Identification of key community structure variables in the Smart Grid adoption process
- Identification of key decision factors in the adoption of Smart Grid related technologies
- Integration of behavioral and social factors into the design and implementation of Smart Grid adoption strategies

4. Descriptions of the methodologies utilized

Method: Participants

USC's Fluor Tower dormitory includes 44 residential suites on 10 floors. With the exception of the first (ground) floor, each floor has six residential suites: one Resident Assistant (RA) suite, one single resident suite, and four group suites housing eight residents each. In total, 300 freshman students living in 39 group suites comprised the target audience for the intervention. Residents of the RA and single suites were excluded from the study because these suites are not instrumented with digital electric meters and it is not possible to track their energy use.

Individuals could participate in the study if they are residents of Fluor Tower and over the age of 18. Competition eligibility was determined by baseline survey completion; in all, 67 residents (22%) from16 suites on six floors completed surveys, and thus were eligible to enter. Involvement was voluntary and informed consent was obtained.

The mean age of the sample was 18.25. Approximately two-thirds of the sample comprised females (66%), and 76% of the sample identified as at least "somewhat" or more liberal political orientation. The ethnic breakdown of the sample was as follows: 11% African American, 13% Asian American, 13% Caucasian, 63% Latino.

Method: Procedures

All study procedures were approved by USC IRB.

A total of 216 digital smart electric smart meters were installed throughout Fluor Tower at the individual-circuit and residential suite level. This allowed building occupants to measure and monitor their energy use in 15-minute intervals in near real time. During the three-week competition (September 11, 2014 - October 1, 2014), Fluor Tower residents competed against one another to reduce their energy consumption. The suite and floor that reduced their energy consumption by the largest percentage (compared to baseline measurements) were declared the winners. Participating winning suite members were awarded three movie passes each, and participating members of the first place floor won a party with food from In-N-Out Burger (approximately $300 value). To encourage involvement, the RAs for the winning suite and floor were awarded $100 towards funding future activities for their floors.

Unbeknownst to residents, their suite-level energy usage was monitored for two weeks prior to start of the competition (August 25 and September 1) to calculate each suite's energy usage baseline. Residents were made aware of the project when they were invited to the "Fluor Tower, Flex Your Power!" competition kick-off. Here, competition rules and details were explained, residents were given the opportunity to ask questions, and were asked to fill out an initial baseline survey, which took approximately 10 minutes. A total of 67 residents filled out this baseline survey. They also received informational materials, including a competition brochure and suggestions for reducing energy use.

At the end of the competition, participants were asked to fill out a second survey so researchers could assess any changes in their opinions and attitudes about energy use and conservation. Approximately 55% of the initial 67 competition participants (37 out of 67) completed the follow-up survey. This survey required approximately ten minutes to complete and was available 24 hours per day for one week after the end of the competition. Surveys were hosted by Qualtrics, a secure software commonly used by university researchers. Individuals viewed an IRB-approved information sheet prior to viewing survey questions.

During the competition, residents were asked to reduce their energy consumption by performing any actions of their choice during the competition period, which also included two voluntary five-hour energy curtailment/DR events, on Saturday, September 13, and Wednesday, September 24.

To monitor their suite and floor competition rankings, participants were encouraged to regularly check the energy dashboard touch-screen kiosk in the building lobby, which displayed suite and floor energy usage in near real-time (data is pass-coded for security and anonymity). Competition messaging, including energy usage feedback, updated weekly rankings, and DR notifications, also were flyered throughout the building, posted to Facebook, and distributed directly to participating residents in their suites. Finally, participants were contacted directly via email. In total, 14 different types of messages - most customized with specific suite/floor energy use data and competition standings - were created (see Materials below and Appendix A).

Method: Materials

A variety of recruitment and on-going competition customized outreach and messaging materials were created and distributed to residents at various points throughout the project (Table 1). A few samples (denoted with *) are included in Appendix A.

Table 1. Outreach Material and Distribution Method

Outreach material type	**Distribution method**
Competition kick-off brochure	Posted around building
Competition FAQs	Posted around building
"Hot Tips" energy reduction flyer	Posted around building
Suite "secret passcodes" notification	Hand delivered
Week 1 feedback notification *	Hand delivered, emailed
Week 2 feedback notification	Hand delivered, emailed
DR event 1 notification flyer	Posted around building
DR event 2 notification flyer *	Posted around building
Winning suite/floor announcement	Hand delivered, emailed, posted around building
Follow-up survey notification	Posted around building, emailed

Baseline and Follow-up surveys

The surveys assessed demographics and attitudes about energy consumption; energy conservation and other pro-environmental behaviors; climate change perceptions; self-efficacy beliefs; group cohesion; and intentions to participant in future energy efficiency projects.

At the end of the competition, participants were emailed a link to an online survey and asked to respond. The second survey assessed their participation, and factors associated with their behavior changes (if any).

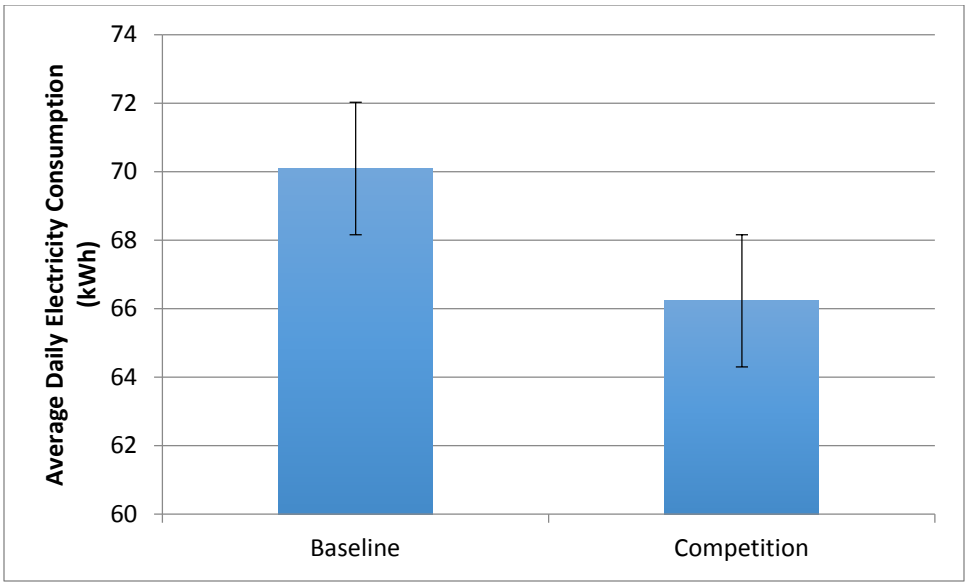
See Appendix B for Baseline and Follow-up surveys.

5. Summaries of the results of the performance of the smart grid systems and technologies derived from lab tests, field tests, or grid-connected applications.

Changes in Energy Consumption

During the competition, suites reduced their energy consumption by an average of 6.4% relative to baseline, saving a total of 3,158 kWh of electricity. This was a significant decline in consumption ($t=2.98$, $p<.01$). This reduction was observed during a heat wave during which an all-time record high electric demand of 6,396 MW for the local utility was observed (on 9/15/14). See results below in Figure 1.

Figure 1. Mean daily electricity consumption in kWh among group suites.



Approximately 64% of suites used less energy during the competition than baseline, with decreases ranging from 13.4 - 40.7%. On the other hand, 36% of suites had increased their consumption, with increases ranging from 6.2 - 21.5%. With a few exceptions, the majority of these suites had no participants in the surveys, suggesting that these suite members passively "opted out" of the study.

DR event participation

A key goal of our DR events was to persuade residents to engage in a simple, 2-step procedure to curtail energy use during DR events. Survey data shed light on compliance rates with these requests. The majority of respondents took part in at least one of the two DR events based on follow-up survey responses. Approximately 67% of respondents reported taking part in both events, 12% participated in only the first, and 3% (1 individual) in only the second DR event. With respect to specific behaviors undertaken, 55% of respondents indicated that they opened their windows the night before the event as instructed, and 35% did so for the second event. This provides preliminary support for specific behavioral requests, but suggests that effects may taper off across repeated occasions. Further research on this issue is needed.

Willingness to Participate in Future Efforts

At follow-up, the majority of participants stated that they were willing to participate in future DR events (79%) and more than half (61%) said they would take part in additional energy efficiency measures on campus.

Engagement in Competition

Respondents checked the kiosk an average of 6.2 (SD=8.5) occasions throughout the 3 weeks. They reported having 11.6 (SD=19.4) conversations with other residents, and 5.9 with RAs.

Changes Observed

Participants reported a significant increase in the frequency of pro-environmental behaviors performed from baseline to follow-up. Importantly, these behaviors included not only those that impacted energy use, but others as well, such as transportation choices, water consumption, and encouraging others to be environmentally responsible. See table 2 for details. This suggests that the energy competition approach may have spill-over effects to non-energy behaviors.

Participants reported a number of notable changes from baseline to follow-up. Additionally, self-efficacy beliefs and group cohesion also increased marginally throughout the intervention. Other relevant motivators of change (e.g., belief in climate change, perceived social norms) also changed in the desired direction (i.e., increased), but these changes did not reach levels of statistical significance. See table 2 below for details.

Table 2. Self-reported behavior and baseline and follow-up (n=33)

	Mean (SD)	t-test results
Pro-environmental behavior[a]		
Time 1	56.88 (10.29)	t=-2.84
Time 2	61.73 (9.76)	p<.01
Group Identification[b]		
Time 1	38.64 (4.48)	t=-1.89
Time 2	40.22 (5.71)	p<.07
Self-efficacy[b]		
Time 1	15.33 (2.31)	t=-1.86
Time 2	16.15 (2.43)	p<.08
Climate change risk perceptions		

Time 1	26.03 (5.19)	t=1.05
Time 2	26.88 (4.70)	p<.31
Perceived general social norms		
Time 1	4.97 (1.21)	t=-.69
Time 2	5.12 (1.08)	p<.50
Perceived provincial social norms		
Time 1	4.91 (1.07)	t=-0.12
Time 2	4.94 (1.06)	p<.91

[a] Significant at α=0.05

[b] Significant at α=0.10

6. Summary of the major findings and conclusions, including lessons learned and best practices.

In summary, electricity use among all suites was approximately 6% lower during the competition period compared to baseline, a significant reduction. This decrease was observed despite record heat and all-time record peak electricity demand in the Southern California region during the competition period. Additionally, participants reported engaging in a variety of specific conservation behaviors significantly more frequently during the competition relative to baseline. Approximately 70% of engaged residents also participated in at least one DR event. In addition, self-efficacy beliefs increased over time. At follow-up, participants also indicated willingness to continue participating in DR events as well as future campus energy efficiency programs.

Limitations

The above findings should be viewed in light of several limitations. First, response bias must be considered. Individuals who elected to participate in the surveys may differ in important ways from individuals who chose not to participate, such as pre-existing level of engagement or interest in energy or sustainability issues. Although we used prizes in an attempt to recruit a broader sample, it is possible that results may not generalize to all populations. In the long term, prizes may not be a feasible nor an effective strategy for sustaining energy conservation, particularly among utility residential customers. Further research into alternatives to incentives is necessary going forward. In addition, our sample size was relatively small. We identified a number of promising trends, but most tests did not reach traditional levels of statistical significance. This underscores the importance of recruitment efforts in these types of studies.

Strengths

This study had a number of strengths:

1. We contribute to a limited body of evidence that supports the effectiveness of dormitory energy competitions in motivating college students to save energy. In addition, dorm energy competitions typically have not targeted peak demand reduction, nor have they investigated specific conservation behaviors performed, leaving unanswered questions about the impacts of these efforts. Our study addressed these limitations, which can help to streamline future interventions. University Housing and Facility staffs may also use the results of this research to inform student programming.

2. Advancing research on energy efficiency interventions, this project is a first step in exploring the effectiveness of energy feedback on promoting participation in DR among college students. We also looked beyond simple energy savings saved to identify specific behaviors performed to achieve usage reductions. Given our limited sample size and the quasi-experimental nature of the present study, future research should continue explore changes in energy use behaviors using an experimental design.

3. Planning and executing the "Fluor Tower, Flex Your Power!" energy competition forged strong bonds of cooperation and collaboration between the research team and USC's Offices of Housing/Resident Life and Facilities Management. This partnership will provide beneficial in future campus test bed energy management experiments.

4. From a practical standpoint, in three weeks, dormitory residents saved 3,158 kWh of electricity compared to baseline, which is equivalent to avoiding the emission of more than 3473 pounds of carbon dioxide. The results of this research provide evidence that real-time smart grid technology-enabled feedback, combined with incentives, can motivate campus residents to reduce energy consumption.

Lessons Learned

- Importance of recruiting to maximize participation
    - One of the limitations of this project was the relatively low survey participation rates. There were several contributors to this issue that could be avoided in future efforts. First, the project was an isolated study, rather than part of a larger effort. It is likely that situating the competition in the context of a broader, more heavily publicized program,

such as Earth Day, or similar, would garner more support and participation. Future efforts should either leverage existing broader-scale programs, or create new ones, either of which could incorporate an energy competition within or between dormitories as one element. Also, garnering the support of motivated, enthusiastic Housing and Residence Life staffs is critical. To ensure adequate intervention participation levels, sufficient resources for staffing and incentives are required.

- Consider competition duration and timing in the calendar year to ensure optimal on-going participation over the duration of the competition.

7. Summary of future plans and next steps with respect to additional testing, demonstration, or deployment

Identifying the psychological correlates of energy behavior change is critical to understanding the mechanisms underlying the change. Knowing how intervention strategies spur and sustain behavior change will enable the development of more streamlined and targeted interventions, and this knowledge will then be used to shape messaging strategies effectively for future energy conservation programs during Operations. The lessons learned from the present project have directly informed our program strategies and messaging plans for Operations. For instance, allotting adequate time and resources towards recruitment will be a key thrust.

8. Appendix: supporting documentation for reference

Appendix A: Messaging and Outreach Materials

Sample: Competition Week 2 Feedback Email

10/5/2014

Subject: Fluor Tower Energy Reduction Competition Weekly Results

Hello!

Your weekly results for the Fluor Tower, Flex Your Power! energy reduction competition are as follows:

Week #1

Suite: 3rd place – 8.01% energy usage increase

Floor: 9st place – 5.03% energy usage increase

Week #2

Suite: 2nd place – 2.9% energy usage decrease

Floor: 8th place – 7.5% energy usage decrease

Floor and suite winners will be announced in mid October and prizes will be awarded at that time.

Thanks for competing – and keep saving energy!

Ellen Dux
Analyst, Consumer Behavior Team
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USC SmartGrid Living Laboratory
http://losangeles.usc.edu

Fluor Tower, Flex Your Power!
Competition Results Week #1



How Did You Do?

Your suite ranked place out of 39 suites

Your suite its energy use by compared to its baseline.

Your floor ranked place out of 10 floors.

Your floor its energy use by compared to its baseline.

REMINDERS

- Check out the Energy Kiosk in the main lobby near the pool table to monitor your suite and floor competition rankings in real time.
- Competition ends October 1 - two weeks to go - keep reducing!
- The winning suite and floor get cool prizes at end of competition.

Fluor Tower, Flex Your Power! competition is a research study; participation is voluntary.

Fluor Tower, Flex Your Power!

USC SmartGrid Living Laboratory

http://losangeles.usc.edu/



Fluor Tower Save Power Hours
Wednesday Sept 24 12p – 5p

Step 1

Tonight, Tuesday Sept 23, **open your windows** so cool air can cool your room. The building will retain the cool air and help your suite maintain a comfortable temperature. Turn off your A/C unit to reduce energy use.

Step 2

Wednesday Sept 24 from 12p – 5p, keep your energy use to a minimum. Turn off your A/C and use fans instead. Hang out in the lobby or library!

The Fluor Tower, Flex Your Power! competition is part of a research study; participation is voluntary.

Appendix B: Baseline and Follow-up Surveys

Fluor Tower Baseline

Q24 University of Southern California Los Angeles Regional Smart Grid Demonstration Project Information Sciences Institute Viterbi School of Engineering University of Southern California 4676 Admiralty Way, Suite 1001 Marina del Rey, CA 90292 INFORMATION SHEET FOR NON-MEDICAL RESEARCH "Fluor Tower, Flex Your Power!" Study ID: UP-14-00446 Valid From: 8/29/2014 to 8/28/2015 PURPOSE OF THE STUDY You are invited to participate in a research study conducted by the Lead of the Decision Systems group, Michael D. Orosz, Ph.D. and Behavioral Scientist Nicole D. Sintov, Ph.D., both of the USC Information Sciences Institute. The study is funded by the United States Department of Energy and the Los Angeles Department of Water and Power (LADWP). Energy systems throughout the country are being updated as technology improves. USC is exploring ways to use emerging technologies to better monitor and supply power to all buildings on and around campus in increasingly energy-efficient ways. We are interested in learning about your opinions regarding energy use and conservation. ELIGIBILITY To participate in this study, you must be at least 18 years of age and a resident of Fluor Tower residence hall on the University of Southern California's University Park Campus. Participating in this study is voluntary. You may terminate your participation at any time. Please read the information below before deciding whether or not to participate. STUDY TASKS Baseline and Follow-up Surveys If you agree to participate in this study, you will be asked to complete a baseline survey that asks questions about your energy usage behaviors, perceptions regarding climate change, and feelings of affiliation with Fluor Tower. You will also be asked to complete a follow-up survey this fall. Each survey is anticipated to take no more than 10 minutes to complete. Energy Reduction Competition You are also being asked to participate in an energy reduction competition being held in Fluor Tower. In the competition, suites compete against one another to reduce their energy use. Likewise, each floor competes against the others to reduce energy use. The suite and floor that reduce their energy consumption by the largest percentage during the competition (compared to baseline) will be declared the winners. You may contribute to reducing your suite/floor energy use by performing any actions you wish. You will receive a "tips" sheet with suggested actions. As part of the competition, you are encouraged to check out the Fluor Tower kiosk, which displays the energy usage among the suites and floors at Fluor Tower. This information is updated in near real-time so you can check your progress in the competition. POTENTIAL RISKS AND DISCOMFORTS There are no anticipated risks to your participation. BENEFITS TO PARTICIPANTS AND SOCIETY You may not directly benefit from your participation; however it is hoped that this study will help the university better manage energy consumption, thereby lessening the carbon footprint. COMPENSATION FOR PARTICIPATION If your suite is declared the winner and you decide to participate in the study by filling out the baseline survey, you will win 3 movie passes. If you do not complete the baseline survey you will not be eligible to win the movie passes. If your floor is declared the winning floor, all residents of your floor will receive an In-N-Out party. You do not have to complete the baseline survey to be eligible for the In-N-Out party. CONFIDENTIALITY Your participation is confidential. The data

will be stored as coded to protect your confidentiality and stored on a password-protected computer. Identifiable information will be destroyed upon completion of the study; the de-identified data will be retained indefinitely and may be used in future research studies. If you do not want the data to be used in future studies, you cannot participate in this study. The members of the project team at USC and at Los Angeles Department of Water and Power, as well as the University of Southern California's Human Subjects Protection Program (HSPP) may access the data. The HSPP reviews and monitors research studies to protect the rights and welfare of research subjects. When the results of the research are published or discussed in conferences, no identifiable information will be used. PARTICIPATION AND WITHDRAWAL Your refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You may withdraw your consent at any time and discontinue participation without penalty. ALTERNATIVES TO PARTICIPATION Your alternative is to not participate in this study. Your relationship with USC will not be affected, whether or not you participate in this study. IDENTIFICATION OF INVESTIGATORS If you have any questions or concerns related to this research, you may contact Nicole D. Sintov, Ph.D., via phone at 310 448 9182 or email at Sintov@usc.edu If you have any questions about your rights as a study subject or you would like to speak with someone independent of the research team to have questions answered about this project, or in the event the research staff cannot be reached, please contact the University Park Institutional Review Board (UPIRB), 3720 South Flower Street #301, Los Angeles, CA 90089-0702, (213) 821-5272 or upirb@usc.edu.

Q2 To verify that you are a legal adult, in what year were you born? Please provide the 4-digit year (e.g., 1992):

Q4 What is your current USC undergraduate student status?

- ❍ Freshman (1)
- ❍ Sophomore (2)
- ❍ Junior (3)
- ❍ Senior (4)

Q3 What is your USC email address?

Q5 What is your Fluor Tower suite number (e.g., 101)?

Q1 The scale below consists of a number of words that describe different feelings and emotions. Read each item and then check the box that most precisely indicates the extent you have felt this way over the past few weeks. Do not think too much about this; respond with what comes to mind naturally.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree or Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
Upset (1)	❍	❍	❍	❍	❍	❍	❍
Hostile (2)	❍	❍	❍	❍	❍	❍	❍
Alert (3)	❍	❍	❍	❍	❍	❍	❍
Ashamed (4)	❍	❍	❍	❍	❍	❍	❍
Inspired (5)	❍	❍	❍	❍	❍	❍	❍
Nervous (6)	❍	❍	❍	❍	❍	❍	❍
Determined (7)	❍	❍	❍	❍	❍	❍	❍
Attentive (8)	❍	❍	❍	❍	❍	❍	❍
Afraid (9)	❍	❍	❍	❍	❍	❍	❍
Active (10)	❍	❍	❍	❍	❍	❍	❍

Q6 To what extent do you agree or disagree with the following statements? Circle one answer per question.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neutral (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
I would describe myself as environmentally responsible (1)	❍	❍	❍	❍	❍	❍	❍
I am concerned about the current environmental state the world is in (2)	❍	❍	❍	❍	❍	❍	❍
I would prefer to be in a different residence hall/dormitory building (3)	❍	❍	❍	❍	❍	❍	❍
I think of Fluor Tower as part of who I am (4)	❍	❍	❍	❍	❍	❍	❍
Residents of Fluor Tower like one another (5)	❍	❍	❍	❍	❍	❍	❍
I see myself as quite different from other residents of Fluor Tower (6)	❍	❍	❍	❍	❍	❍	❍
I enjoy interacting with the residents of	❍	❍	❍	❍	❍	❍	❍

Fluor Tower (7) I don't think of Fluor Tower as part of who I am (8)	❍	❍	❍	❍	❍	❍	❍
I don't like many of the other people who live in Fluor Tower (9)	❍	❍	❍	❍	❍	❍	❍
I see myself as quite similar to other residents of Fluor Tower (10)	❍	❍	❍	❍	❍	❍	❍

Q7 How often have you done each of the following in the past few weeks?

	Never (1)	Rarely (2)	Sometimes (3)	Fairly Often (4)	Very Often (5)
Recycled (1)	❍	❍	❍	❍	❍
Encouraged friends or family to recycle (2)	❍	❍	❍	❍	❍
Conserved gasoline by walking or bicycling (3)	❍	❍	❍	❍	❍
Wrote a letter or email, or endorsed a petition on a website in support of an environmental issue (4)	❍	❍	❍	❍	❍
Volunteered time to help an environmental group (5)	❍	❍	❍	❍	❍
Left lights on in a room that nobody was in (6)	❍	❍	❍	❍	❍
Used task lighting (lighting appropriate for a specific activity such as a reading lamp to read) instead of overhead lighting (7)	❍	❍	❍	❍	❍
Let the water	❍	❍	❍	❍	❍

run while I was brushing my teeth (8)					
Littered (9)	❍	❍	❍	❍	❍
Turned on the air conditioner when I felt warm (10)	❍	❍	❍	❍	❍
Shut off my computer when I was not using it (11)	❍	❍	❍	❍	❍
Unplugged devices that were not in use (e.g., DVD player, TV, printer, etc) (12)	❍	❍	❍	❍	❍
Opened windows or used fans instead of turning on air conditioning (13)	❍	❍	❍	❍	❍
Made a special effort to minimize energy use during a hot day (14)	❍	❍	❍	❍	❍
Encouraged others in my suite to conserve energy (15)	❍	❍	❍	❍	❍
Made a special	❍	❍	❍	❍	❍

effort to take shorter showers (16)					

Q8 Lady Gaga is the current United States president.

- ❍ True (1)
- ❍ False (0)

Q9 Please indicate the extent to which each of the following statements is true for you.

	Not at all True (1)	Hardly True (2)	Moderately True (3)	Exactly True (4)
I am confident that I could deal efficiently with unexpected events. (1)	❍	❍	❍	❍
Thanks to my resourcefulness, I know how to handle unforeseen situations. (2)	❍	❍	❍	❍
I can remain calm when facing difficulties because I can rely on my coping abilities. (3)	❍	❍	❍	❍
If I am in trouble, I can usually think of a solution. (4)	❍	❍	❍	❍
I can usually handle whatever comes my way. (5)	❍	❍	❍	❍

Q10 To what extent are you concerned about air pollution in your city?

- ❍ Completely Unconcerned (1)
- ❍ Unconcerned (2)
- ❍ Somewhat Unconcerned (3)
- ❍ Neutral (4)
- ❍ Somewhat Concerned (5)
- ❍ Concerned (6)
- ❍ Extremely Concerned (7)

Q11 How serious a threat is climate change to humankind?

- ❍ Not at all Serious (1)
- ❍ Not Serious (2)
- ❍ Not Very Serious (3)
- ❍ Neutral (4)
- ❍ Somewhat Serious (5)
- ❍ Serious (6)
- ❍ Very Serious (7)

Q12 How well is climate change understood by science?

- ❍ Not Understood At All (1)
- ❍ Not Understood (2)
- ❍ Not Well Understood (3)
- ❍ Neutral (4)
- ❍ Understood (5)
- ❍ Well Understood (6)
- ❍ Very Well Understood (7)

Q13 How much does the idea of climate change fill you with dread?

- ❍ Not Dread At All (1)
- ❍ No Dread (2)
- ❍ Not Much Dread (3)
- ❍ Neutral (4)
- ❍ Some Dread (5)
- ❍ Dread (6)
- ❍ A Lot of Dread (7)

Q14 To what extent do you have moral concern about climate change?

- ❍ No Moral Concern At All (1)
- ❍ No Moral Concern (2)
- ❍ Not Much Moral Concern (3)
- ❍ Some Moral Concern (4)
- ❍ Moral Concern (5)
- ❍ Strong Moral Concern (6)
- ❍ Very Strong Moral Concern (7)

Q15 I plan to participate in Fluor Tower Save Power Hours.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Somewhat Disagree (3)
- ❍ Neutral (4)
- ❍ Somewhat Agree (5)
- ❍ Agree (6)
- ❍ Strongly Agree (7)

Q16 I plan to participate in energy efficiency projects on campus.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Somewhat Disagree (3)
- ❍ Neutral (4)
- ❍ Somewhat Agree (5)
- ❍ Agree (6)
- ❍ Strongly Agree (7)

Q17 People in my general social environment (e.g., family, friends, classmates, coworkers) support my efforts to save energy.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Somewhat Disagree (3)
- ❍ Neutral (4)
- ❍ Somewhat Agree (5)
- ❍ Agree (6)
- ❍ Strongly Agree (7)

Q18 People in Fluor Tower support my efforts to save energy.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Somewhat Disagree (3)
- ❍ Neutral (4)
- ❍ Somewhat Agree (5)
- ❍ Agree (6)
- ❍ Strongly Agree (7)

Q19 Tell us about yourself. As with all questions in this survey, you may skip any questions you prefer not to answer

Q20 What is your gender?

- ❍ Male (1)
- ❍ Female (0)

Q21 What do you consider to be your political orientation?

- ❍ Very Liberal (1)
- ❍ Liberal (2)
- ❍ Somewhat Liberal (3)
- ❍ Moderate (4)
- ❍ Somewhat Conservative (5)
- ❍ Conservative (6)
- ❍ Very Conservative (7)

Q22 With which ethnic category do you most strongly identify?

- ❍ African or African American (1)
- ❍ Asian or Asian American (2)
- ❍ Caucasian/White (3)
- ❍ Latino/a (4)
- ❍ Native American / Pacific Islander (5)
- ❍ Multiracial (6)
- ❍ Other (7) _____

FOLLOW-UP SURVEY

Fluor Tower Follow-up

Q3 What is your USC email address?

Q5 What is your Fluor Tower suite number (e.g., 101)?

Q1 The scale below consists of a number of words that describe different feelings and emotions. Read each item and then check the box that most precisely indicates the extent you have felt this way over the past few weeks. Do not think too much about this; respond with what comes to mind naturally.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree or Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
Upset (1)	❍	❍	❍	❍	❍	❍	❍
Hostile (2)	❍	❍	❍	❍	❍	❍	❍
Alert (3)	❍	❍	❍	❍	❍	❍	❍
Ashamed (4)	❍	❍	❍	❍	❍	❍	❍
Inspired (5)	❍	❍	❍	❍	❍	❍	❍
Nervous (6)	❍	❍	❍	❍	❍	❍	❍
Determined (7)	❍	❍	❍	❍	❍	❍	❍
Attentive (8)	❍	❍	❍	❍	❍	❍	❍
Afraid (9)	❍	❍	❍	❍	❍	❍	❍
Active (10)	❍	❍	❍	❍	❍	❍	❍

Q6 To what extent do you agree or disagree with the following statements? Circle one answer per question.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neutral (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
I would describe myself as environmentally responsible (1)	❍	❍	❍	❍	❍	❍	❍
I am concerned about the current environmental state the world is in (2)	❍	❍	❍	❍	❍	❍	❍
I would prefer to be in a different residence hall/dormitory building (3)	❍	❍	❍	❍	❍	❍	❍
I think of Fluor Tower as part of who I am (4)	❍	❍	❍	❍	❍	❍	❍
Residents of Fluor Tower like one another (5)	❍	❍	❍	❍	❍	❍	❍
I see myself as quite different from other residents of Fluor Tower (6)	❍	❍	❍	❍	❍	❍	❍
I enjoy interacting with the residents of	❍	❍	❍	❍	❍	❍	❍

Fluor Tower (7) I don't think of Fluor Tower as part of who I am (8)	❍	❍	❍	❍	❍	❍	❍
I don't like many of the other people who live in Fluor Tower (9)	❍	❍	❍	❍	❍	❍	❍
I see myself as quite similar to other residents of Fluor Tower (10)	❍	❍	❍	❍	❍	❍	❍

Q7 How often have you done each of the following in the past few weeks?

	Never (1)	Rarely (2)	Sometimes (3)	Fairly Often (4)	Very Often (5)
Recycled (1)	❍	❍	❍	❍	❍
Encouraged friends or family to recycle (2)	❍	❍	❍	❍	❍
Conserved gasoline by walking or bicycling (3)	❍	❍	❍	❍	❍
Wrote a letter or email, or endorsed a petition on a website in support of an environmental issue (4)	❍	❍	❍	❍	❍
Volunteered time to help an environmental group (5)	❍	❍	❍	❍	❍
Left lights on in a room that nobody was in (6)	❍	❍	❍	❍	❍
Used task lighting (lighting appropriate for a specific activity such as a reading lamp to read) instead of overhead lighting (7)	❍	❍	❍	❍	❍
Let the water	❍	❍	❍	❍	❍

run while I was brushing my teeth (8)					
Littered (9)	❍	❍	❍	❍	❍
Turned on the air conditioner when I felt warm (10)	❍	❍	❍	❍	❍
Shut off my computer when I was not using it (11)	❍	❍	❍	❍	❍
Unplugged devices that were not in use (e.g., DVD player, TV, printer, etc) (12)	❍	❍	❍	❍	❍
Opened windows or used fans instead of turning on air conditioning (13)	❍	❍	❍	❍	❍
Made a special effort to minimize energy use during a hot day (14)	❍	❍	❍	❍	❍
Encouraged others in my suite to conserve energy (15)	❍	❍	❍	❍	❍
Made a special	❍	❍	❍	❍	❍

effort to take shorter showers (16)					

Q8 Lady Gaga is the current United States president.

- ❍ True (1)
- ❍ False (0)

Q9 Please indicate the extent to which each of the following statements is true for you.

	Not at all True (1)	Hardly True (2)	Moderately True (3)	Exactly True (4)
I am confident that I could deal efficiently with unexpected events. (1)	❍	❍	❍	❍
Thanks to my resourcefulness, I know how to handle unforeseen situations. (2)	❍	❍	❍	❍
I can remain calm when facing difficulties because I can rely on my coping abilities. (3)	❍	❍	❍	❍
If I am in trouble, I can usually think of a solution. (4)	❍	❍	❍	❍
I can usually handle whatever comes my way. (5)	❍	❍	❍	❍

Q10 To what extent are you concerned about air pollution in your city?

- ❍ Completely Unconcerned (1)
- ❍ Unconcerned (2)
- ❍ Somewhat Unconcerned (3)
- ❍ Neutral (4)
- ❍ Somewhat Concerned (5)
- ❍ Concerned (6)
- ❍ Extremely Concerned (7)

Q11 How serious a threat is climate change to humankind?

- ❍ Not at all Serious (1)
- ❍ Not Serious (2)
- ❍ Not Very Serious (3)
- ❍ Neutral (4)
- ❍ Somewhat Serious (5)
- ❍ Serious (6)
- ❍ Very Serious (7)

Q12 How well is climate change understood by science?

- ❍ Not Understood At All (1)
- ❍ Not Understood (2)
- ❍ Not Well Understood (3)
- ❍ Neutral (4)
- ❍ Understood (5)
- ❍ Well Understood (6)
- ❍ Very Well Understood (7)

Q13 How much does the idea of climate change fill you with dread?

- ❍ Not Dread At All (1)
- ❍ No Dread (2)
- ❍ Not Much Dread (3)
- ❍ Neutral (4)
- ❍ Some Dread (5)
- ❍ Dread (6)
- ❍ A Lot of Dread (7)

Q14 To what extent do you have moral concern about climate change?

- ❍ No Moral Concern At All (1)
- ❍ No Moral Concern (2)
- ❍ Not Much Moral Concern (3)
- ❍ Some Moral Concern (4)
- ❍ Moral Concern (5)
- ❍ Strong Moral Concern (6)
- ❍ Very Strong Moral Concern (7)

Q15 I plan to participate in future Fluor Tower Save Power Hours.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Somewhat Disagree (3)
- ❍ Neutral (4)
- ❍ Somewhat Agree (5)
- ❍ Agree (6)
- ❍ Strongly Agree (7)

Q16 I plan to participate in energy efficiency projects on campus.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Somewhat Disagree (3)
- ❍ Neutral (4)
- ❍ Somewhat Agree (5)
- ❍ Agree (6)
- ❍ Strongly Agree (7)

Q17 People in my general social environment (e.g., family, friends, classmates, coworkers) support my efforts to save energy.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Somewhat Disagree (3)
- ❍ Neutral (4)
- ❍ Somewhat Agree (5)
- ❍ Agree (6)
- ❍ Strongly Agree (7)

Q18 People in Fluor Tower support my efforts to save energy.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Somewhat Disagree (3)
- ❍ Neutral (4)
- ❍ Somewhat Agree (5)
- ❍ Agree (6)
- ❍ Strongly Agree (7)

Q31 Did you receive your suite's secret code for the kiosk?

- ❍ Yes (1)
- ❍ No (0)

Q30 How many times did you check the kiosk since the competition launched?

Q26 Excluding RAs and RCs, how many conversations did you have with other residents in your building about the competition?

Q33 How many conversations did you have with RAs/RCs for your building about the competition?

Q34 Did you participate in Save Power Hours #1 on Sunday September 14th?

- ❍ Yes (1)
- ❍ No (0)

If No Is Selected, Then Skip To Did you participate in save power eve...

Q35 If yes, what actions did you take? Select all that apply.

- ❑ Opened windows the night before (1)
- ❑ Turned off A/C in my room (2)
- ❑ Turned off A/C in common areas (3)
- ❑ Minimized A/C in my room (4)
- ❑ Minimized A/C in common areas (5)
- ❑ Encouraged my suite mates to reduce their energy consumption (6)
- ❑ Left my suite and went to common area with the explicit purpose of saving energy (e.g., lobby, library, dining establishment) (7)
- ❑ Other (8) _____

Q36 Did you participate in Save Power Hours #2 on Wednesday September 24th?

- ❍ Yes (1)
- ❍ No (0)

If No Is Selected, Then Skip To Did you see the feedback flyer 1 that...

Q37 If yes, what actions did you take? Please select all that apply.

- ❍ Opened windows the night before (1)
- ❍ Turned off A/C in my room (2)
- ❍ Turned off A/C in common areas (3)
- ❍ Minimized A/C in my room (4)
- ❍ Minimized A/C in common areas (5)
- ❍ Encouraged my suite mates to reduce their energy consumption (6)
- ❍ Left my suite and went to common area with the explicit purpose of saving energy (e.g., lobby, library, dining establishment) (7)
- ❍ Other (8) _____

Q38 Did you see the Results Flyer #1 that was slipped under your suite door Saturday September 20th?

- ❍ Yes (1)
- ❍ No (0)

Q39 Did you see the Results email #1 that was sent on Saturday September 20th?

- ❍ Yes (1)
- ❍ No (0)

Q40 Did you see the Results flyer #2 that was slipped under your suite door on Saturday September 27th?

- ❍ Yes (1)
- ❍ No (0)

Q41 Did you see the Results email #2 that was sent on Saturday September 27th?

- ❍ Yes (1)
- ❍ No (0)

Q42 Did you see the Save Power Hours flyer #1 that was posted around Fluor Tower on Saturday September 13th?

- ❍ Yes (1)
- ❍ No (0)

Q44 Did you see the Save Power Hours flyer #2 that was posted around Fluor Tower on Tuesday September 23rd?

- ❍ Yes (1)
- ❍ No (0)

9. Acknowledgements

We thank the USC Housing and Facilities Management Offices for their valuable input and support throughout the Fluor Tower energy competition. Specifically, Jack Trump and his staff of Resident Assistants, and Carol Fern and her staff at Facilities Management.

Appendix M Final Technical Report Use Case DR-6

Final Technical Report

Los Angeles Department of Water & Power Smart Grid Regional Demonstration Project

Demand Response

Use Case DR-6



Prepared by

Viterbi School of Engineering DR Research Team

Viktor K. Prasanna, Principal Investigator

June 30, 2016

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13 APPENDIX ERROR! BOOKMARK NOT DEFINED.

1 Summary

The goal of this demonstration was to show an integrated SG infrastructure that can accept DR control signals from LADWP and perform targeted load curtailment across campus, while considering the curtailment potential available in buildings across campus and the preferences of the facility users. In addition, this would also demonstrate the Micro-Grid acting as a utility operations center in making DR decisions. The purpose of the DR software architecture was to assist the USC facility operations in determining when to perform load curtailment and by how much based on CCF, assist in selecting the buildings and people to target for curtailment, provide suggestions on direct and voluntary curtailment strategies, and continuously monitor the effectiveness of obtaining the curtailment.

The intended outcome of this demonstration was to provide LADWP with performance data for a range of load curtailment strategies for different building types and building control technologies. The specific studies on the USC Micro-Grid address the required demonstrations stated in Section 3.5.1.5 of the SOPO.

2 DR Optimization in Campus Test Bed Micro-Grid using Service-Based Software Architecture (DR-6)

New developments in technology on the customer and utility sides of the meter offers the potential for the sophisticated integration of demand-side resources into utility operations to support improved grid reliability, cost containment, reduction of Green House Gas (GHG) emissions, and integration of renewable energy resources. These DR technologies are by definition smart grid (SG) technologies, purposed for active monitoring and dynamic control of electricity usage.

Technological advances such as bi-directional smart meters allow remote monitoring and control, thus transforming the traditional power grids into complex cyber-physical systems. Reliable operation of a power grid requires utilities to dynamically meet the fluctuating energy demand with supply (possibly fluctuating due to the stochastic nature of renewable energy generation). If demand exceeds the generation capacity, the utility must buy extra power from the spot market at higher rates in order to avoid power outages and ensure grid reliability. Typically, the power consumption profiles of the customers are such that their peak power consumptions overlap during certain periods of a day. We refer to such periods as peak demand periods. The cumulative demand from customers in the grid might exceed the generation capacity of the utility during such periods.

Analytics based on real-time and historic power system data provide utility control center operators with forecasting and visualization tools to increase the accuracy and reliability of load management decisions. Smart meters and advanced building and home automation systems provide customers with unprecedented levels of convenience and control to manage how and when energy is used.

Building and home automation, smart charging and discharging of electric vehicles, distributed generation, and Micro-grids all create new opportunities and new challenges for grid operations and optimization.

Demand Response (DR) is a widely used technique to ensure grid stability with minimal expenditure. Instead of focusing on increasing the generation capacity, DR focuses on reducing the grid consumption by either incentivizing or penalizing customers. Utilities enroll customers into DR programs and signals them during peak periods in response to which the customers curtail their demands. Traditionally, DR

implementations require advanced planning and notification. However, the community is progressing towards Dynamic Demand Response where the utility needs to schedule and implement a DR in few hours of notice due to dynamically changing grid conditions.

The utility needs accurate energy consumption prediction to determine when to schedule a DR event along with the amount of curtailment required given the generation capacity. A customer participating in a DR event can adopt one of the several available strategies to curtail consumption. Strategies are actions such as turning down the air conditioner, dimming the lights which lead to reduction in power consumption. The utility needs to accurately estimate the reduced consumption/curtailment achieved by each customer strategy pair to make informed customer-strategy pair selection to achieve the required curtailment value.

Accurate and efficient prediction of energy consumption for individual customers is critical for a successful DR event. Availability of energy consumption data from smart meters in finer granularity (15 minutes) offers us a unique challenge to apply forecasting models. Historically, coarse-grained energy consumption prediction of total utility area are performed using data available at feeder and sub-station level that is collected by the SCADA system. Prediction models at building 1 levels are more prone to intra-day and seasonal variability and hence pose a greater challenge for developing accurate prediction models.

Prediction techniques such as time series models are unsuitable for reduced consumption prediction due to abrupt changes in customer profile during the DR event start and end and insufficient recent observations within a DR window for training a model. Alternate approach is to use the historical consumption profiles of the building-strategy pairs to predict the reduced consumption (hence curtailment) during the DR event. A challenge in such an approach is that the reduced consumption is affected significantly by factors such as environmental conditions on DR day, day of the week the

DR is observed etc. In this paper, we briefly discuss the Direct Curtailment Forecasting Model [7] which we developed for accurate prediction of reduced consumption during DR event. Selecting the right set of customer-strategy pairs to achieve a targeted curtailment value is critical for the success of a DR Event. The availability of smart controllers and meters with fine-grained customer control capability can be leveraged to offer customers a dynamic range of curtailment strategies that are feasible for small durations within the overall DR event.

The goal of the DR Project was to demonstrate how some of the most promising new and emerging DR technologies can be applied to best address opportunities and challenges using facilities at the University of Southern California main and health campuses. Specifically, the goal of the DR Project was to show an integrated SG infrastructure that can accept DR control signals from LADWP and perform targeted load curtailment across the USC campus, while considering the curtailment potential available in buildings across campus and the preferences of the facility users. This would also demonstrate the Micro-Grid acting as a utility operations center in making DR decisions. Demonstrations include:

- The use of historical and real-time data collected from Advanced Metering Infrastructure (AMI) to provide power system control operators with real-time information tools for making outage and load management decisions, including initiating DR events, performing dynamic adaptations to changing conditions during demand response events, and performing post analysis of the response to these events.
- Demonstrate automated DR by (i) enabling the USC campus testbed Micro-grid accept DR control signals from LADWP, and (ii) performing automated targeted load curtailment across campus, while considering the curtailment potential available in buildings and the preferences of the facility users.

We have implemented a Demand Response program on our campus micro-grid to demonstrate its large scale feasibility and identify and resolve the challenges associated with practical deployment. Our Demand Response technique uses learning of occupant energy strategy preferences (at fine grained scales ranging from buildings to floor levels within buildings) to make accurate electricity consumption predictions and individual curtailment recommendations using only a small subset of consumption data.

3 Key Demonstration Objectives

The key objectives of this demonstration are listed below:

1. Demonstrate a full campus-wide integrated SG infrastructure incorporating both existing and new information systems.
2. Demonstrate targeted load curtailment, using different types of load profiles and customer service requirements, different facility configurations, and different strategies.
3. Demonstrate DR events and processes, highlighting seamless operation of services-based architecture, granularity of load control, cyber security controls, and compliance with customer's load profiles and service requirements.

Table 1: Description of the steps for its successful completion:

SOPO Demonstrations	Functions To Be Demonstrated	Use Case Scenarios	Key Steps
• **Campus test bed microgrid demonstration: React reliably and precisely to a demand response event from the utility by activating procedures to curtail demand.**	1. Demonstrate a full campus-wide integrated Smart Grid infrastructure incorporating both existing and new energy and information systems. 2. Demo targeted load curtailment, using different types of load profiles and customer service requirements, different facility configurations, and different network technologies and strategies. 3. Demo demand response events and	(Shared) DR-1-Scenario 3: Data Integration, Load Forecast and DR Optimization for Demand-side Load Management	Receive Analysis report of datasets in DWP DR Smart Grid program (Data will be collected after 1st DR event) Defining experiments to evaluate the DR optimization on LADWP relevant to the DR use case studies in DR design document Designing demonstration scenarios, objectives, metrics and goals on LADWP. Update the prediction models and their configuration based on USC microgrid experimental results (USC has submitted papers already / currently doing ongoing studies)

	processes, highlighting seamless operation of services-based architecture, granularity of load control, cyber security controls, and compliance with customer's load profiles and service requirements.		Tune the DR policy engine configuration in USC microgrid based on demonstration goals. Advise operational team from LADWP on configuring the demand response decision support (DDS) from the admin interface based on demonstration goals. (3Di work) Technical report on demand response Decision Support (DDS) engine on LADWP. (Report will come when DDS is functional and DR events executed) Technical report on experimental results on campus related to DR use case studies in DR design Doc. (Will come when USC DR events executed)

4 Scenarios

Scenario 1: Reliable and Precise Responses to Utility Demand Curtailment Events

1. USC Demo Control / Visualization Center JACE controller queries the DRAS on a prescribed time cycle.
2. LADWP Smart Grid Control Center (SGCC) sends out a request for DR providing curtailment information including event initiation time and duration via the DRAS.
3. USC Demo Control Center receives the DR event signal which notifies selected USC facility personnel of the request.
4. An acknowledgement is sent from the USC Control Center back to LADWP acknowledging and accepting participation in the curtailment event.
5. USC facility personnel select pre-defined curtailment strategies that have determined based on previous building curtailment experiments. Selection is based on the time period between signals received time and event initiation time and the duration of the event. The curtailment is initiated manually while leveraging the programming that has been put in place in the BAS to invoke the DR strategies at each building.

6. USC Control Center monitors the load curtailment, PQ and building space conditions as reported by BAS. For those systems selected for participation in the DR event, the control system automatically adjusts the operation of the systems to maintain space conditions within pre-established limitations.
7. Complaints from occupants during the DR event is noted by facility personnel and used to modify future DR strategies, or if at unacceptable levels, the current strategy.
8. The effect of the curtailment is recorded for future analysis. This includes the drop in electricity demand, the impacts to the space conditions of spaces (temperature, light levels etc.), and comparison of load reduction between buildings to improve DR strategy deployment.

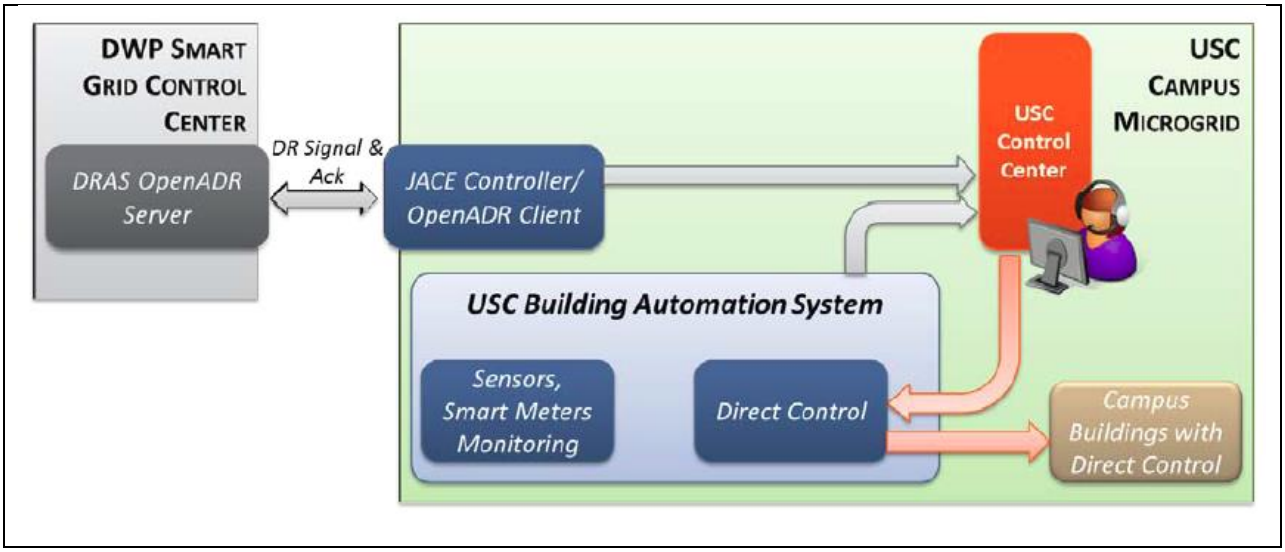


Figure 1: Functions to be Demonstrated in USC Campus Microgrid

For satisfying the DR-6-Scenario 1 use case the following targets were delivered:

- USC demo/control center JACE controller can query the DRAS (Demand Response Automation Server) in a timely schedule.
- LADWP can send out requests for DR, provided the information includes time and duration
- USC control center can receive the DR event and notify selected USC facility personnel
- An acknowledgement is sent from USC to LADWP
- USC facility personnel can select pre-defined curtailment strategies that have determined based on previous building curtailment experiments.
- Selection is based on the time period between received time and event initiation time and the duration of the event.
- Curtailment is fully automated by integrating FMS control system with DDS and the policy engine to invoke available DR strategies for each building.
- USC control center can monitor the load curtailment and building conditions.
- USC facility operator can select and observe the current load status and kW.

- For those buildings automatically selected for participation in the DR event by the policy engine, the control system can automatically adjust the operation of the buildings to maintain conditions within pre-established limitations.
- FMS can monitor complaints from building occupants during the DR for modifying future DR strategies, or if at unacceptable levels, the current strategy.
- Record the effect of the curtailment for future analysis (including temperature, demand, lightings, etc.)
- Comparisons can be made between buildings to improve DR strategy.
- Facility operator can be notified of available Load curtailment and forecasted consumption through automated software architecture.
- Facility operator can pull up the historical consumptions and forecast consumptions.
- Facility operator has a list of curtailment options available and can choose different curtailment strategies or request a set to be suggested.
- The effectiveness of curtailment is available to the operator and it is updating during the DR event to improve the performance and accuracy.
- All DR activities are monitored and recorded for future use, and are available to LADWP for informing the operations at the utility.

To demonstrate the above targets for automated DR with predictive load curtailment, an overall communications platform was developed, as shown in the figure below, to support decision making after a demand response event has been initiated.

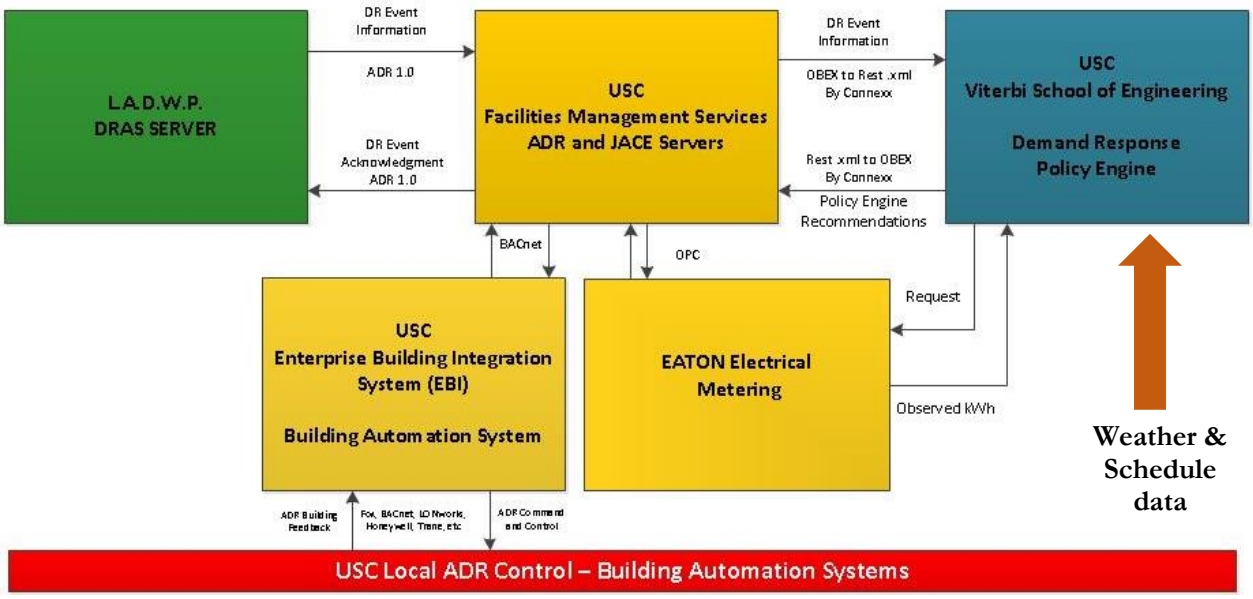


Figure 2: DR Communication Process Flow Chart

Upon receipt of a pending ADR event, communication between the FMS Demand Response servers and the USC Viterbi School of Engineering Demand Response Policy engine is initiated, where a list of potential buildings for DR is offered to the policy engine for selection in the DR event and for estimating the load curtailment. The list of "selected" buildings and the "selected" demand response strategy for each is communicated back to the FMS Demand Response servers. The load curtailment projection is communicated to the LADWP DRAS. At the start time of the DR event, the FMS Demand Response servers communicate to the building level control systems to initiate the pre-programmed demand response strategies. These strategies are implemented until the end of the DR event. Throughout the event, the Policy Engine polls the electrical meters to report back the "achieved" load curtailment, and to make any adjustments in building or DR strategy selected to achieve the projected load curtailment. At the end of the event, a final electrical meter read is performed to provide the realized load curtailment. This realized DR load curtailment information is communicated back to the LADWP DRAS.

The developed USC DR software architecture is shown below:

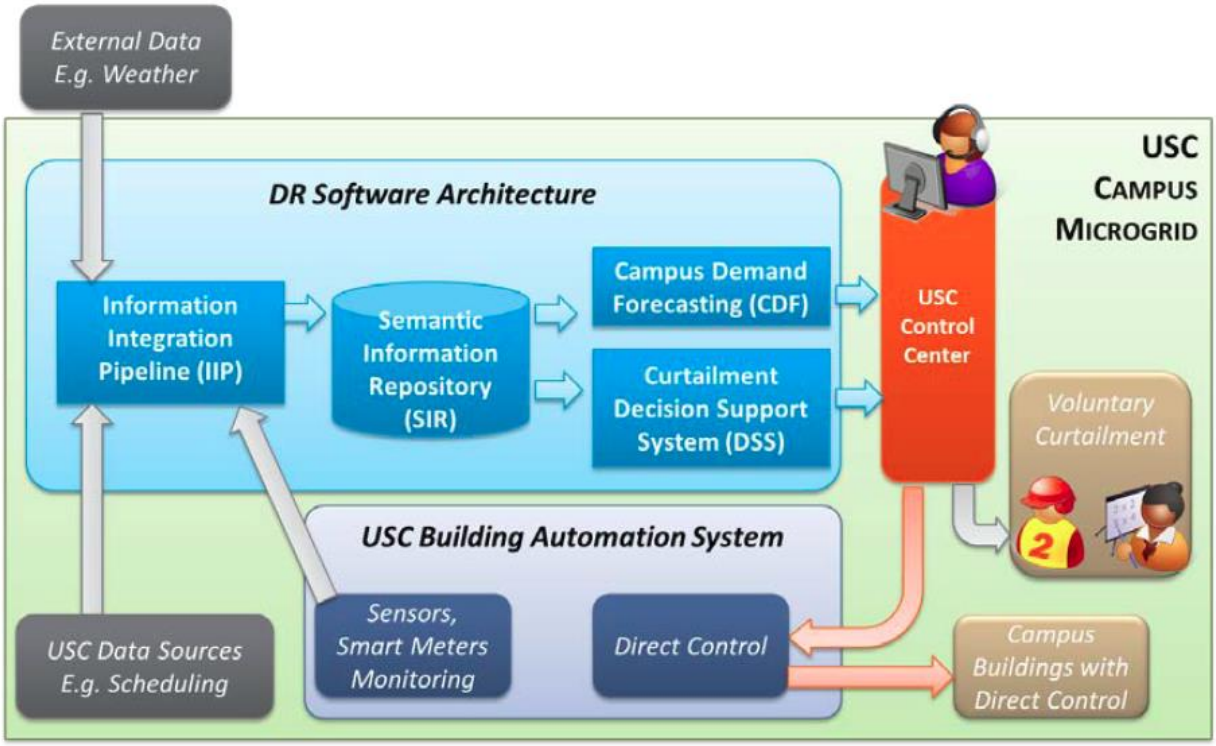


Figure 3: USC DR Software Architecture

Scenario 2: Load Demand Forecast and Curtailment Strategy Selection using Software Architecture

1. USC Facility Operator observes the current load status of the campus from the USC demo control center. This displays the real-time load (KW) on different buildings and equipment within them, the current consumption demand (KWh) from the different buildings and the forecast consumption (KWh). The facility operator can look at information at different spatial granularities of rooms/buildings/regions of campus based on available information. This information is provided by the BAS, the Semantic Information Repository (SIR) and the CCF component.

2. The facility operator uses static knowledge of available generation capacity (simulated) and the forecasted consumption to determine that a curtailment is necessary on the campus. The software architecture will also be automatically monitoring for such a situation and will notify the operator through an alarm if it is detected. The operator will be provided with an estimate of the shortfall in capacity and the period for which it will last.
3. The facility operator can pull up the historical consumption and forecasted consumption for the campus to verify that a curtailment is necessary, and initiate curtailment operations.
4. The facility operator will be assisted in curtailment selection by the DSS of the software architecture. The DSS will provide different categories of curtailments strategies, along with an estimate of the level of curtailment from each, how soon the curtailment can be achieved, the probability of success and the impact on user comfort. These curtailment opportunities will be tuned for the current conditions on campus, and include both direct load control and voluntary control. Direct control strategies that are suggested will include both coarse grained direct control for different buildings as well as fine grained opportunities that exist in individual floors or equipment. Voluntary control will identify individuals or building managers who can be contacted for requesting curtailment.
5. The operator will have the choice to individually select from the different curtailment strategies or request a set of strategies to be suggested by the DSS to meet the required curtailment. Once the choice is made, the curtailment will be executed. Direct control operations will be initiated using the BAS. Voluntary curtailment operations will be initiated using electronic communication through email or smart phone.
6. The effectiveness of the curtailment will be monitored by the operator by observing the current load in the different buildings on which curtailment has been started and matching it against the expected curtailment from those buildings. Execution of the direct control operation will be verified through observations of load and equipment activity. Information for this will come from the BAS and SIR.
7. The operator will be able to observe if the curtailment is not going to be achieved. The DSS will also provide notification if the curtailment target is beyond acceptable thresholds. This will allow the operator to steer the curtailment strategy, similar to step 4.
8. All DR activities will be monitored and recorded to allow future analysis by the operator and for automated learning by the DSS. This will also be provided to LADWP for informing DR operations at the utility.

The USC DR Software was used to satisfy the DR-6-Scenario 2 use case. Specifically, the following targets were delivered:

- USC Facility operator can observe the current load status of the campus from the USC demo control center. This displays the real-time load (KW) on different buildings and equipment within them, the current consumption demand (KWh) from the different buildings and the forecast consumption (KWh).
- The facility operator can look at information at different spatial granularities of rooms/buildings/regions of campus based on available information. This information is provided by the Semantic Information Repository and the machine learnt models component.

- The facility operator uses static knowledge of available generation capacity (simulated) and the forecasted consumption to determine that a curtailment is necessary on the campus.
- The facility operator is assisted in curtailment selection by the DDS component of the USC software architecture.
- DSS can provide different categories of curtailment strategies, along with an estimate of the level of curtailment from each, how soon the curtailment can be achieved, the probability of success and the impact on user comfort.
- The operator can individually select from the different curtailment strategies or request a set of strategies to be suggested by DSS to meet the required curtailment.
- Once the selection of buildings is performed, the curtailment policy is automatically executed.
- The effectiveness of the curtailment is monitored by the operator by observing the current load in the different buildings on which curtailment has been started and matching it against the expected curtailment from those buildings.
- Execution of the direct control operation is verified through observations of load and equipment activity.
- The operator can observe if the curtailment is not going to be achieved.
- All DR activities are monitored and recorded to allow future analysis by the operator and for automated learning by DSS. This is also provided to LADWP for informing DR operations at the utility.

5 Methodology

To demonstrate use case 1 and 2 described above, and meet the success criteria for this demonstration, the USC VSoE team developed "Demand Response Decision Support" (DDS), a Java library that integrates machine learning techniques for consumption and curtailment prediction as well as for consumer and DR strategy selection algorithms, and "Policy Engine", a recommendation software that provides suggestions on curtailment actions that can be taken to meet a given target based on current and historical conditions so as to assist facility operations in determining how much load to curtail based on Campus Consumption Forecasting (CCF). An Automated Programing Interface (API) has been delivered to LADWP. The software architecture (policy engine) provides a recommendation in selecting the buildings to target for curtailment, continuously monitoring the effectiveness of obtaining the curtailment target, and dynamically adapting its recommendations to ensure the curtailment target is met. Specifically, the purpose of the DR software architecture was to assist the USC facility operations in determining when to perform load curtailment and by how much based on CCF, assist in selecting the buildings and people to target for curtailment, provide suggestions on direct and voluntary curtailment strategies, and continuously monitor the effectiveness of obtaining the curtailment. This enabled the team to precisely and reliably respond to utility DR events with an appropriate forecasting and curtailment strategy.

6 Success Criteria

The success criteria for the USC VSoE team included the successful completion of all related use cases. Successful communication between Facility Management System (FMS) and the ability to remotely control and monitor individual buildings according to received curtailment strategies during DR periods. Additionally, as part of this demonstration, the USC VSoE team was responsible for providing the LADWP with performance data for a range of load curtailment strategies for different building types and building control technologies. The specific studies on the USC Micro-Grid address the required demonstrations stated in Section 3.5.1.5 of the SOPO.

DDS is integrated with the FMS control center as a REST service (representational state transfer) which receives as input consumption data and DR requirements (e.g., duration, start time, available buildings and strategies) and returns the recommended list of building-strategies to be used to reach the desired curtailment target.

The DR Software architecture demonstrates the microgrid acting as a utility operations center in making DR decisions, and assists the USC FMS operations in determining when and how much load curtailment on which buildings should happen. DDS also has to continuously monitor the effectiveness of obtaining the curtailment.

The functional target of this demonstration is as follows:

- Demonstrate a full campus wide integrated SG infrastructure incorporating old and new information systems
- Demonstrate targeted load curtailment using different types of load profiles, customer service requirements and facility configurations, and strategies.
- Demonstrate DR events and processes, highlighting seamless operation of service based architecture, granularity of load control, cyber security and compliance with customers' load profiles and service requirements.

In addition to the success criteria described above, the USC VSoE team developed a set of metrics to evaluate the accuracy of the predictive models they developed to enable automated and dynamic decision making for Demand Response. Inherently, this process, which is shown in the Figure below is a Big Data driven process.

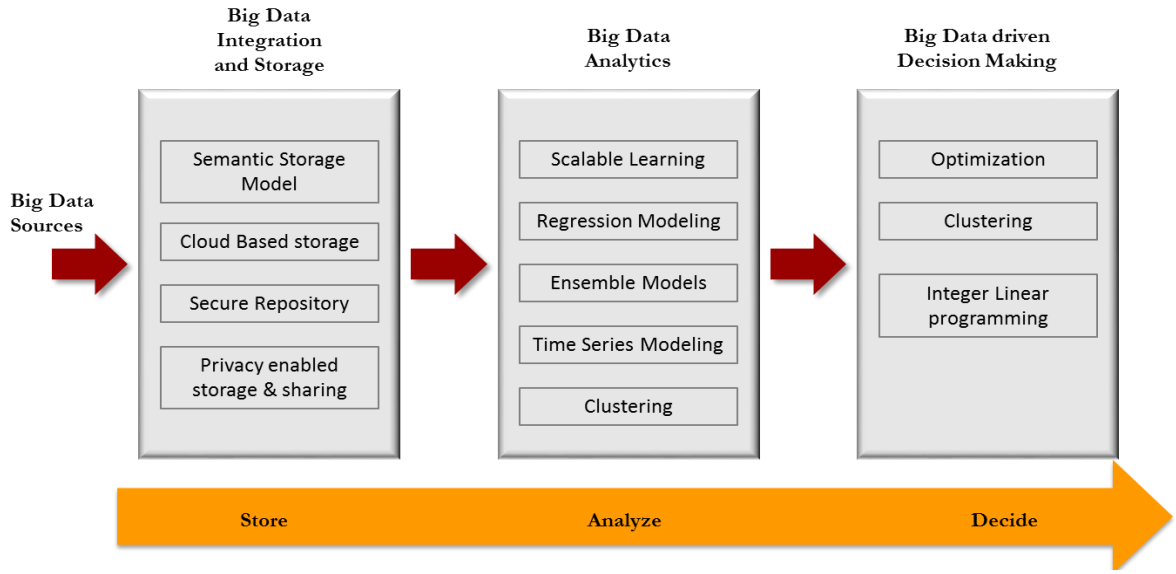


Figure 4: Big Data driven Decision making for Demand Response

The steps of this complex process are shown in the figure below:

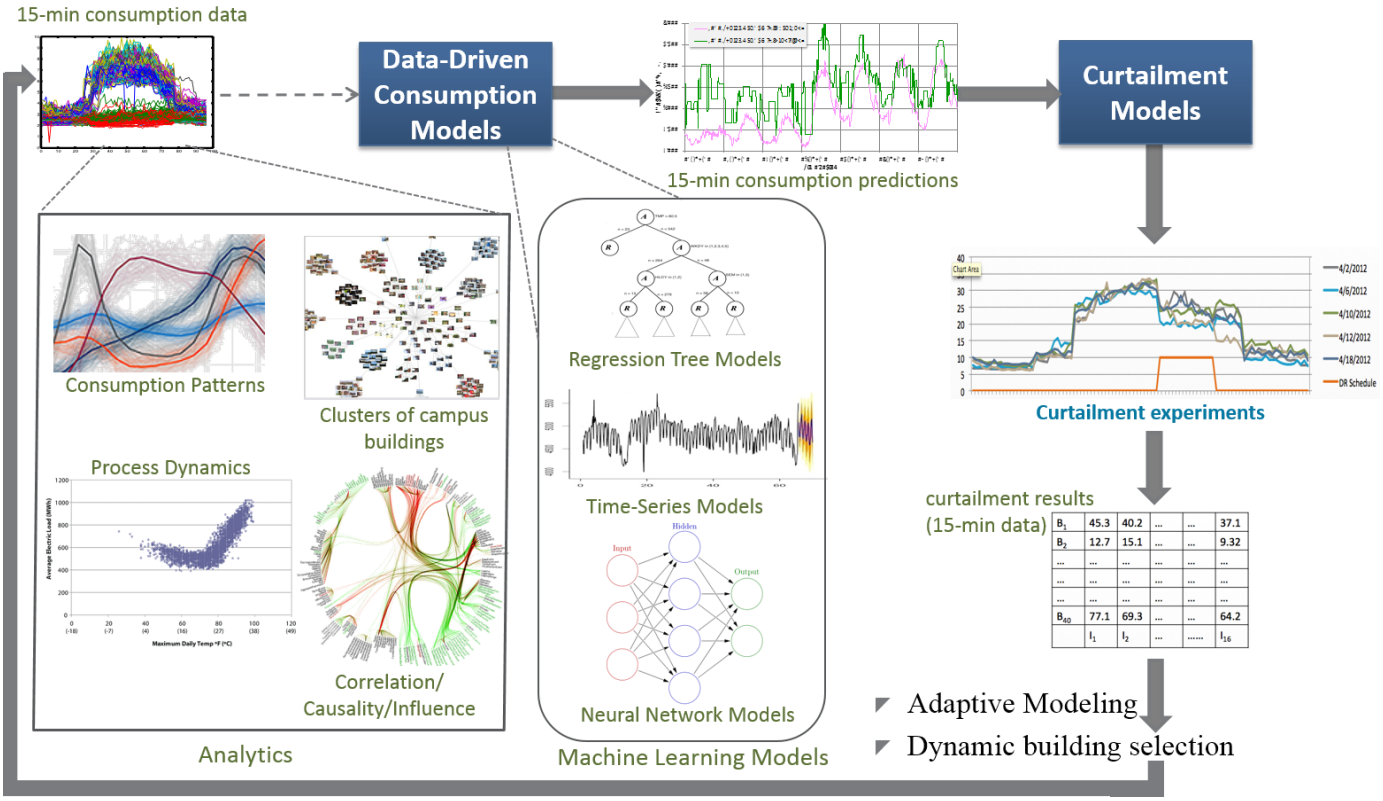


Figure 5: The Cycle of Big Data driven Decision making for Demand Response

To perform a meaningful evaluation and selection of the developed prediction models, the USC VSoE team proposed a suite of both application independent and dependent performance measures to rationally compare models along the dimensions of scale independence, reliability, volatility and cost. These measures include:

- Mean Absolute Percentage Error (MAPE): A simple to interpret variant of MAE, normalized by the observed value at each interval, thus providing scale independence.
- Coefficient of Variation of RMSE (CVRMSE): An unbiased estimator that incorporates both the prediction model bias and its variance, and gives a unitless percentage error measure.
- Relative Improvement (RIM): A simple, unitless, relative measure for reliability that complements error measures in cases where being accurate more often than a baseline is useful, and occasional large errors relative to the baseline are acceptable.
- Volatility Adjusted Benefit (VAB): A measure for reliability that captures how consistently a candidate model outperforms a baseline model by normalizing the model's error improvements over the baseline by the standard deviation of these improvements. This relative measure offers a "risk adjusted" scale independent error value.
- Computation Cost (CC): The cost for training and predicting using a model can prove important when it is used either at large scales and/or in real-time applications that are sensitive to prediction latency.
- Data collection Cost (CD): Rather than examining the raw size of data used for training or predicting using a model, a more useful measure is the effort required to acquire and assemble

the data. Size can be managed through cheap storage but collecting the necessary data often requires human and organizational effort. The USC VSoE team proposed a scale-dependent measure of data cost defined in terms of the number of unique values of features involved in a prediction model.

- Total Compute Cost (TCC): An estimate of the total running cost of using a model for a duration of time.
- Domain Bias Percentage Error (DBPE): An indicator of predictions being positively or negatively biased compared to the observed values. This measure can be important when over or under-prediction errors, relative to observed, have a non-uniform impact on the application.
- Reliability Threshold Estimate (REL): An estimate of how frequently errors fall within a predetermined threshold.
- Cost-Benefit Measure (CBM): The cost of a model relative to the gains it provides. CBM compares candidate models having different error measures and costs to evaluate which provides a high reward for a unit compute cost spent.

7 Demonstration Environment

The UPC campus of USC is really a "City inside a city" consisting of 301 acres, over 100 buildings including residential facilities, office/classroom, restaurants, laboratories, baseball and football fields, swimming pool in a very urban environment. We have over 33,000 students and 13,000 faculty and staff either living or commuting to campus with a high international student and faculty representation, mirroring LA and its diverse culture. We are LADWP's largest single private institutional customer with a peak demand of over 25 megawatts.

The USC campus Micro-Grid test bed is a SG environment with diverse building and people profiles, and provides a controlled setting for conducting experiments and demonstrations. To this end, the USC Micro-Grid has in place its own BAS that allows the facility operators to remotely monitor, control and communicate with individual buildings, and play a role similar to a utility system operator that can make decisions on DR optimization on the campus. In addition, the campus is a large private customer of LADWP that can receive and enact curtailment strategies during DR periods.

We own our own electrical infrastructure. We receive power at two locations at 34.5kV, step down to 4.8kv for distribution throughout the campus. We manage and maintain all of the feeders, circuits, and responsibility for balancing the loads. We do not generate any electricity on campus – at this time, but are looking towards PV systems. We monitor the electrical usage, using revenue quality meters for each building, both for billing purposes and for efficiency evaluations. These meters also provide power factor and harmonic distortion information that we can study as part of load shedding and impacts to the overall grid system.

USC Microgrid as a Smart Grid Testbed

Largest single private institutional customer of LADWP

- Electric peak load of 28 MW
- Annual consumption of 210 million kWh of electricity

Diversity

- Buildings (Dorms, Classrooms, Labs, Hospital buildings, Restaurants, Public transportation, Offices,…)
- Demographics

Scale

- 45K+ population
- ~50K sensors and smart meters
- 170 Buildings

Smart Equipment

- Measure energy usage at 1 min intervals
- Central control for zone temperatures and HVAC, VFD equipment, etc.



City within a City

A Living and Learning Lab

Smart Grid Test-bed

8 Technologies Developed and Deployed

USC DR Software Architecture

To develop an automated demand response with predictive load curtailment, an overall communications platform was developed to support decision making after a demand response event has been intiatiated. Upon recept of a pending ADR event, communication between the FMS Demand Response servers and the USC Viterbi School of Engineering Demand Response Policy engine is initiated, where a list of potential buildings for DR is offered to the policy engine for selection in the DR event and for estimating the load curtailment. The list of "selected" buildings and the "selected" demand response strategy for each is communicated back to the FMS Demand Response servers. The load curtailment projection is communictated to the LADWP DRAS. At the start time of the DR event, the FMS Demand Response servers communicate to the building level control systems to initiate the pre-programmed demand response strategies. These strategies are implemeneted until the end of the DR event. Throughout the event, the Policy Engine polls the electrical meters to report back the "achieved" load curtailment, and to make any adjustments in building or DR strategy selected to achieve the projected load curtailment. At the end of the event, a final electrical meter read is performed to provide

the realized load curtailment. This realized DR load curtailment information is communicated back to the LADWP DRAS.

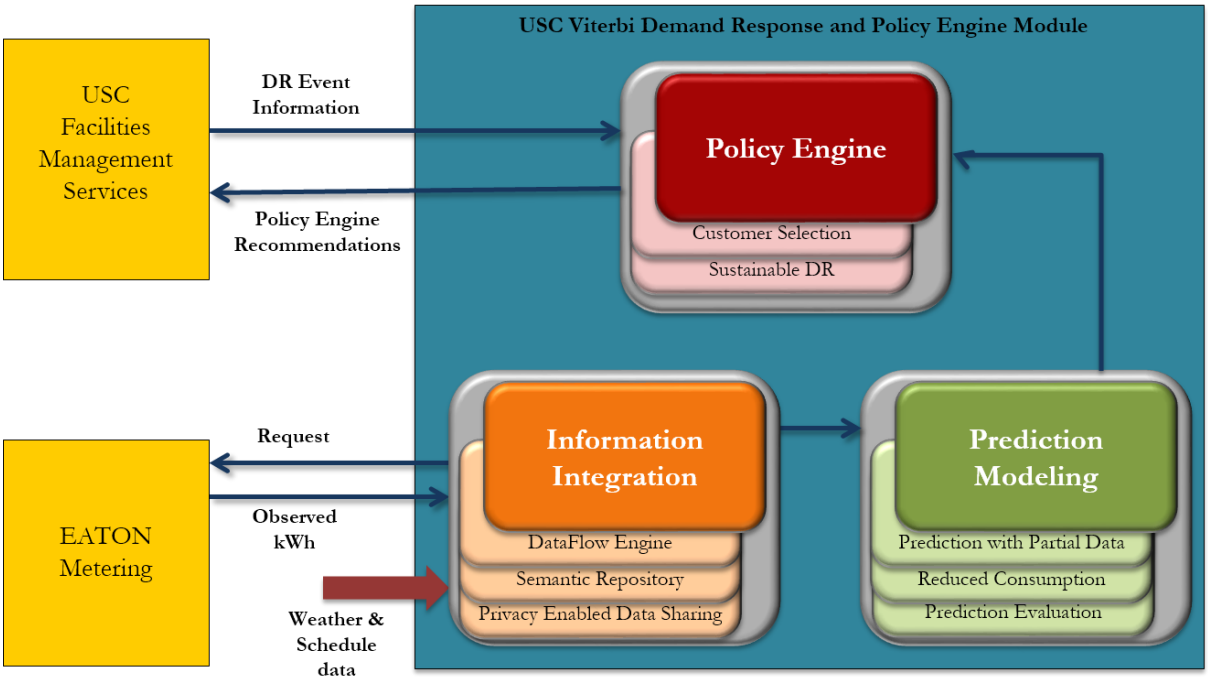


Figure 6: USC DR Software Control and Data Flow

The DR Software Architecture contains the following components, summarized in table xx:

- Information Integration Pipeline (IIP): This is a modular and extensible framework for configuring new information sources that will be ingested. It is responsible for getting all relevant data for performing DR from external data sources in real-time using different protocols, parsing their structural formats, performing semantic annotations and updating the historical database. The semantic ontology is a predefined description of the knowledge and relationships between the acquired information that allows users to interpret the information. The use of semantic ontology serves to enhance the interoperability of the software architecture and easily map external domain concepts to a uniform global vocabulary, and when necessary, extend the ontology itself. Information from sources outside USC, the BAS and other sources within USC such as classroom scheduling will be acquired using this pipeline.
- Database of historical training data for consumption forecasting: This is a database for storing and accessing information present in the DR software architecture for use by forecasting and curtailment applications. This also provides data required by the control center operator for visualization. Besides information from the IIP, it also records the DR curtailment actions that were initiated and the actions performed by the users and on the buildings as part of curtailment.
- Collection of machine learned models for consumption prediction: This component provides consumption forecasts for the campus, at different spatial and temporal granularities.

Specifically, forecasting can be performed at the campus or building levels, and for day ahead and hour ahead. Our models use information that is continuously updated to improve forecasting accuracy.

- Collection of machine learned models for curtailment prediction: This component provides curtailed consumption forecasts for campus buildings. Forecasting can be performed at the building level during the day of a DR event. During a far request a preliminary estimate is provided, which is subsequently adjusted to refltect the effetc of factors such as temperature and occupancy that affect the level of consumption and curtailment potential of a building. Our model uses information that is continuously updated to improve forecasting accuracy.
- DDS: Java library that we have developed to integrate machine learning techniques for consumption and curtailment prediction as well as for consumer and DR strategy selection algorithms.
- Policy Engine: This component provides suggestions to the control center operator on the curtailment actions that can be taken to meet a given target based on current and historical conditions. Curtailment values are based on transient direct control curtailment opportunities with minimal impact on user comfort, and direct control over facilities based on building response models. This provides a list of suitable targets for achieving the curtailment. An adaptive algorithm that uses prior knowledge of responses to curtailment has been developed to improve suggestions over time.

Table 2: Major DR Software Architecture Components Functionality

Component	Functionality
Machine Learned Model Training	Update load forecast models using data from Information Repository Forward updated load forecast models to Information Repository
Consumption Forecasting	Predict customer load using real-time energy consumption data and historical data from the Information Repository. Consumption forecasts for the campus are perfoemd at different spatial and temporal granularities. Specifically, forecasting can be performed at the campus (i.e., aggregate consumption) or individual building levels, and for day ahead and hour ahead. Our models use information that is continuously updated to improve forecasting accuracy.
Curtailed Consumption Forecasting	Predict expected customer reduced consumption during DR using real-time energy consumption data and data from Repository. Curtailment values are based on transient direct control curtailment opportunities with minimal impact on user comfort, and direct control over facilities based on building response models. This provides a list of suitable targets for achieving the curtailment. An adaptive algorithm that uses prior knowledge of responses to curtailment has been developed to improve suggestions over time. Specificcally, forecasting can be performed at the building level during the day of a DR event. During a far request

	a preliminary estimate is provided, which is subsequently adjusted to refltect the effect of factors such as temperature and occupancy that affect the level of consumption and curtailment potential of a building. Our models use information that is continuously updated to improve forecasting accuracy.
Consumer Selection for Curtailment	Use customer load forecast, reduced consumption prediction, and their prior response to DR recorded in the information repository to optimally select customers who receive the DR signal
Information Repository	This database is used for storing and accessing information present in the DR software architecture for use by forecasting and curtailment applications. It also provides data required by the control center operator for visualization. Besides data gathered from smart meters and/or related to prediction models, it also records the DR curtailment actions that were initiated and the actions performed by the users and on the buildings as part of curtailment. It also stores the machine learnt load forecast models for consumption and curtailment prediction as well as statistics of customer adaptation to curtailment over multiple DR events.
Information Integration Pipeline	This is a modular and extensible framework for configuring new information sources that are ingested and integrated with the Information Repository. It is responsible for getting all relevant data for performing DR from external data sources in real-time using different protocols, parsing their structural formats, performing semantic annotations and updating the historical database. Is uses an Ontology to achieve this task. An Ontology is a predefined description of the knowledge and relationships between the acquired information that allows users to interpret the information. The use of semantic ontology serves to enhance the interoperability of the software architecture and easily map external domain concepts to a uniform global vocabulary, and when necessary, extend the ontology itself. Information from sources outside USC, and other sources within USC such as classroom scheduling are acquired using this pipeline.

Demand Decision Support (DDS)

DDS is a Java library that the USC VSoE team has developed to integrate machine learning techniques for consumption and curtailment prediction as well as for consumer and DR strategy selection algorithms. DDS is responsible for managing datasets required for training and prediction, storing and selecting trained models, providing an interface for admins to train and test models, and offering a web service endpoint for automated responses for training and prediction.

The data sources involved in this process are considered “Big Data”. Big data is a broad term for data sets so large and complex that traditional data processing applications are inadequate.

The data sources are listed as following, and are scalable to the level of City of Los Angeles:

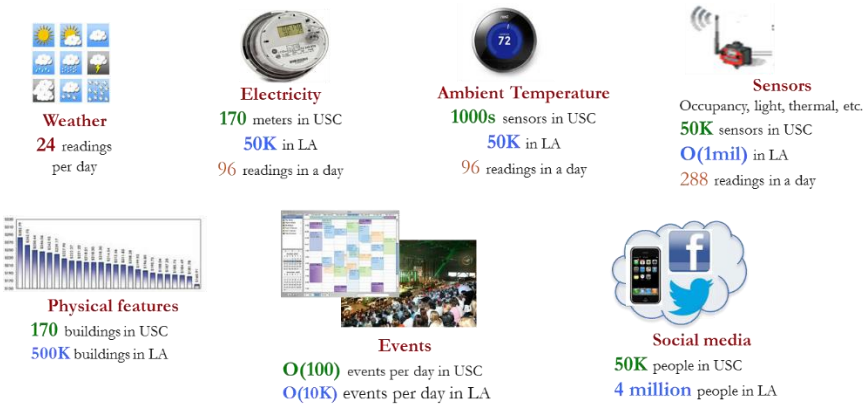


Figure 7 Data and deployed Technologies

Data from sensors is collected in near real-time (every 15 minutes).

DDS is currently integrated with the FMS control center as a REST service which receives as input consumption data and DR requirements (e.g., duration, start time, available buildings and strategies) and returns the recommended list of building-strategies to be used to reach the desired curtailment target.

The objective of developing DDS was to integrate this software within the LADWP workflow. At LADWP, the software is designed to import historical and real-time data, such as AMI, CIS and weather data, for forecasting load demand at the customer level. The information can be displayed as a “heat map” using the Space-Time Awareness Server (STAS) visualization software. The load forecast and generation capacity information is to be used by the system operator to determine when there is going to be a peak load at a certain substation in a future time and load curtailment is necessary. The operator can use the feeder-level load forecast information to determine which feeders and subsets of customers connected to the feeders have good potential for load curtailment. The decision is made by the DR Consumer Selection component. The system operator initiates DR on the selected customers and sends this

request through STAS applications and DRAS server. The operator observes the subsequent reduction in energy consumption, which is displayed using the STAS visualization program.

DDS consists of multiple internal components whose functionality is provided in the table below:

Table 3: DDS Components and Functionality

Components	Functionality
USC DDS Java Kernel Library	Perform training of Java consumption models using provided training datasets Perform training of Java compliance models using provided training datasets Perform prediction of consumption values using provided Java consumption models and prediction datasets Perform prediction of compliance values using provided Java compliance models and prediction datasets
Data Access and Loading	Access external, DWP and project data sources to retrieve latest values. Transform incoming data formats and units into a form that matches the DRDR schema, and load data into DRDR database Allow bulk and periodical access and loading.
DRDR Database & Model Store	Provide a database with the appropriate schema for storing and querying training and prediction datasets, and a storage location for trained models.
Data Querying & Model Storage	Performs queries over DRDR databases to return *consistent* training and prediction datasets that are aggregated and gap filled. Supports storing and retrieval of Java model objects.
DDS Web Service	Web service implementation that allows training and prediction using the DDS Java kernel libraries for consumption and compliance. Performs querying of training or prediction data, executing model training and model storage, and invoking model predictions.

The key predictive models that have been developed and integrated with DDS, and their interconnections are shown below:

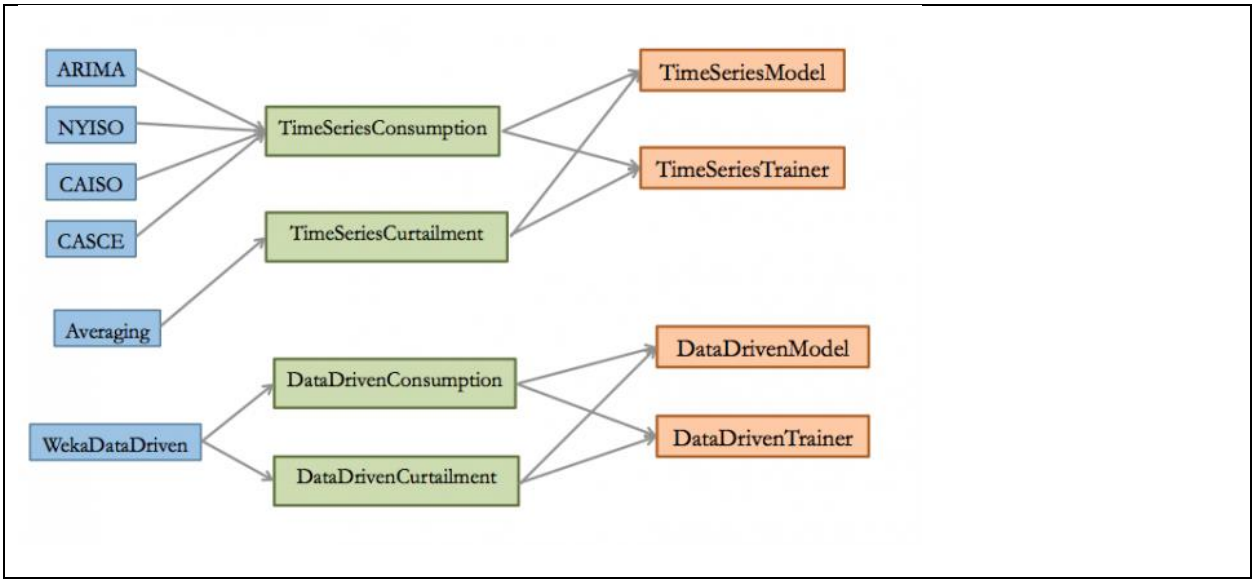


Figure 8: Key Models in DDS

DDS Input

DDS takes input from the FMS database through queries. The input data has three fields: timestamp (indicating the date and 15-minute time interval), consumption value (in kilo-watt-hours), and quality value (either 0 or 1). The quality value of 1 indicates there is some error in the data and in that case, some interpolation is performed.

DDS Output

The prediction output from the DDS is used in the Policy Engine for decision making about which buildings & strategies to use.

Major DR DDS Components and Functionality

Table 3: Major DDS Functionality

Components	Functionality
DDS	KWh consumption estimates KWh compliance estimates

Table 4: Major DDS components Functionality

Components	Functionality
USC DDS Java Kernel Library	Perform training of Java consumption models using provided training datasets Perform training of Java compliance models using provided training datasets Perform prediction of consumption values using provided Java consumption models and prediction datasets Perform prediction of compliance values using provided Java compliance models and prediction datasets
Data Access and Loading	Access external, DWP and project data sources to retrieve latest values. Transform incoming data formats and units into a form that matches the DRDR schema, and load data into DRDR database Allow bulk and periodical access and loading.
DRDR Database & Model Store	Provide a database with the appropriate schema for storing and querying training and prediction datasets, and a storage location for trained models.
Data Querying & Model Storage	Performs queries over DRDR databases to return *consistent* training and prediction datasets that are aggregated and gap filled. Supports storing and retrieval of Java model objects.
Administrative Interface	(Browser based) Administrative interface for On-demand model training & testing, Comparison of accuracy of model results, and configuring standard models.
DDS Web Service	Web service implementation that allows training and prediction using the DDS Java kernel libraries for consumption and compliance. Performs querying of training or prediction data, executing model training and model storage, and invoking model predictions.

USC DDS Training and Prediction Java Kernel Library

The DDS Java kernel library from USC offers an API and implementation for consumption and curtailment training and prediction. The library operates using in-memory Java objects and file based

datasets, and should be invoked by other components that can provide the training and prediction datasets, and can store and access trained models.

There are four capabilities that the DDS kernel library provides: Consumption Model Training, Consumption Prediction, Compliance Model Training, and Compliance Prediction.

The DDS Java library has dependencies on several external packages, including the R Statistical Toolbox and Weka Java library.

Consumption Models Training and Prediction:

Consumption training is responsible for building and returning a Java model object that can perform consumption predictions i.e. for a given time period and set of customers, this model predicts the KWh used by individual customers at a certain time granularity (either 1/15min or 1/24hrs). There are two types of models: *data-driven models* that can make prediction at arbitrary time periods given the data features for that time period, and *timeseries models* that can make predictions for consecutive time intervals given the recent historical time intervals. There are two other categorization of models: *dynamic models* that require prior training and *static models* that can be used without training. Dynamic models require to be trained before they can be used for predictions. The training interface accepts as input the type of model algorithm to use for training, configuration parameters for the model algorithm, and the training dataset used to build the model. Models may be trained for individual customers, for a set of customers (e.g. of the same type, in the same distribution area), or for all customers in the service area. The prediction interface for a (trained or static) model accepts as input the time period for making the prediction, the granularity of predictions and the set of dataset features required for the prediction.

Timeseries/Static Models:

These consumption models are used as baseline models by utilities for determining what the consumption would have been for a particular curtailment period. Three baseline model algorithms are provided by the DDS Java library: **California ISO, New York ISO, and Southern California Edison**. These models do not require training and can be used as such.

Timeseries models require the KWh consumption values for recent time intervals to be passed in order to predict the subsequent time intervals. For e.g., the last 10 days of KWh values at 15 min intervals may be required to predict the next 24 hrs of KWh values. The number of historical intervals required for prediction depends both on the model and the number of future intervals to predict. Timeseries models typically do not offer accurate predictions for more than 24hrs into the future.

```
ITimeSeriesConsumptionTrainer {
	IConsumptionModel trainConsumption(Dataset data, ConsumptionInterval interval,
		Map<String, String> modelOptions)
	throws DDSConsumptionException;
}
```

A sample java interface for making predictions using the timeseries models is:

```
ITimeSeriesConsumptionPredictor {
      List<Consumption> predictConsumption(IConsumptionModel predictionModel,
            List<Consumption> historicalConsumption,
            Date predictionStartTime, Date predictionEndTime,
            ConsumptionInterval interval)
      throws DDSConsumptionException;
```

Timeseries/Dynamic Model:

This timeseries consumption model uses the **ARIMA Statistical Model** for making predictions. It is a dynamic model, so it has to be trained before being used for predictions. It uses only historical interval data for training, so the only features present in the training data are the timestamp and KWh usage value for a customer for a certain (historical) time period. The trained model can then be used for making predictions.

Autoregressive Integrated Moving Average (ARIMA) is a time series prediction model, used for forecasting. An ARIMA model is defined in terms of three non-negative parameters: p (the autoregressive order, that denotes the number of past observations included in the model), d (the number of times a time series needs to be differenced to make it stationary), and q (the moving average order that denotes the number of past white noise error terms included in the model).

These parameters are determined using the autocorrelation and partial autocorrelation functions, using the Box-Jenkins test. Given a time series of real numbers X_t, the ARIMA model is defined as:

$$\left(1 - \sum_{i=1}^{p'} a_i L^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t,$$

where L is the lag operator, α_i are the parameters of the autoregressive part of the model, θ_i are the parameters of the moving average part and ε_t are error terms. The lag operator is defined as $L^i y_t = y_{t-i}$.

Data-driven/Dynamic Models:

Data-driven dynamic models use machine learning to train the model using a set of feature vectors provided for each consumption interval. For e.g., a feature vector for a KWh consumption for a particular customer and a particular time interval could be **<customer type, customer zipcode, outside temperature, day of the week>**. Some of the feature vectors may change rarely (e.g. customer type and zipcode may not change for a given customer) while others may change more often (e.g. outside temperature may change every our). Such models often improve in accuracy as larger training datasets are available. We use the **Regression Tree Algorithm** for training the data-driven, dynamic model, and making predictions.

In linear regression, a real-valued variable Y (e.g., electric consumption) is modeled as a linear function of a real-valued variable X, plus noise: $Y = \beta_0 + \beta_1 X + \varepsilon$. In case of multiple variables having an additive effect on Y, linear regression can still be applied as follows: $Y = \beta_0 + \beta^T X + \varepsilon$, where X denotes a vector

containing the values of variables X_1, X_2, X_k. When many variables interact in complicated, nonlinear ways, assembling a linear model can be very difficult. In such cases it might be better to divide the space into smaller regions where interactions are simple enough to be adequately modeled by simple models.

A regression tree (RT) model is used to model such complex data (i.e., several real-valued and/or categorical features) that cannot be effectively modeled by linear regression. An RT model is "learned" by recursively partitioning the training data into smaller regions until they can be represented by a constant or a linear model. The recursion is completed when features at a node are all associated with the same target variable value, or when splitting does not enhance the prediction. At the end, each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf.

A sample java interface for training and making predictions using the data-driven model is:

```
IDataDrivenConsumptionTrainer {
	IConsumptionModel trainConsumption(Dataset data,
		Date trainingStartTime, Date trainingEndTime,
		ConsumptionInterval interval,
		Map<String, String> modelOptions)
	throws DDSConsumptionException;
}
```

```
IDataDrivenConsumptionPredictor {
	List<Consumption> predictConsumption(IConsumptionModel trainModel,
		List<FeatureVector> predictionFeatures,
		Date predictionStartTime, Date predictionEndTime,
		ConsumptionInterval interval)
	throws DDSConsumptionException;
}
```

Curtailed Consumption Models Training and Prediction:

This model averages historical curtailment values by adjusting the number of curtailment intervals. The inputs are the Historical Curtailment Data, Prediction Start Time, Prediction End Time, DR Event Start Time and DR Event End Time. The output is the predicted array of curtailment values.

Curtailment Prediction: Using the past curtailment data, predict the curtailment for today's DR. A pre-defined baseline is required to calculate the curtailment against.
Curtailed-Consumption based Prediction: Using the past consumption data during DR event, predict today's reduced consumption. Use a pre-defined baseline to calculate the curtailment by subtracting the predicted reduced consumption.

Compliance Training and Prediction:

Compliance training is responsible for building and returning a Java model object that can perform compliance predictions i.e. for a given time period and customer, this model predicts the KWh that can be curtailed by that customer with a certain probability. Compliance prediction models require training based on historical responses to prior DR curtailment signals sent to the customer

The compliance training interface accepts as input the type of model algorithm to use for training, configuration parameters for the model algorithm, and the training dataset used to build the model. The training dataset incudes prior curtailment responses for the customer, types of signals/messages sent, and other features about the customer.

Static Timeseries Model:

This model is a **baseline compliance model** that uses a weighted average of responses from a particular customer to determine their future responses. It is a timeseries model and does not consider additional features of the customer in its predictions.

Dynamic Data-driven Models:

We use the **k-means clustering algorithm** for extrapolating from a set of customers with a deep history of known compliance responses to a wide set of customers for whom responses may be sparse or missing. This model improves in accuracy as more curtailment experiments are performed for all customers in the service area.

A second model that DDS supports is **customer behavior compliance models** that take into account responses from surveys and experiments performed by the USC VSoE team. These data-driven models are trained using survey responses from customers correlated against their observed curtailment responses.

Customer Selection and the Policy Engine

The Policy Engine (PE) accepts the FMS request and provides campus wide curtailment strategy policy recommendations for each available building. The recommendations are based on the analysis of the historical consumption data per building and observed curtailment values per building strategy pair. We developed a change making problem based heuristic for customer selection in a DR event which addresses the question: how a given amount of money can be made using the least amount of coins? The coins are the available customer-strategy pairs and their value is the predicted reduction per interval. The customers are grouped into bins which are differentiated by their bin value. The US coin set is used to determine the bin range corresponding to a bin value. The participating customers are grouped in the same bin if their reduction estimate, which we call representative, falls in the corresponding bin range. After the distribution step, customers are paired with the strategy that approximates most closely the bin value (upper bin range). The level of approximation is calculated using the euclidean distance of the corresponding curtailment vector from the bin value. The bins are indexed greedily to achieve the given target.

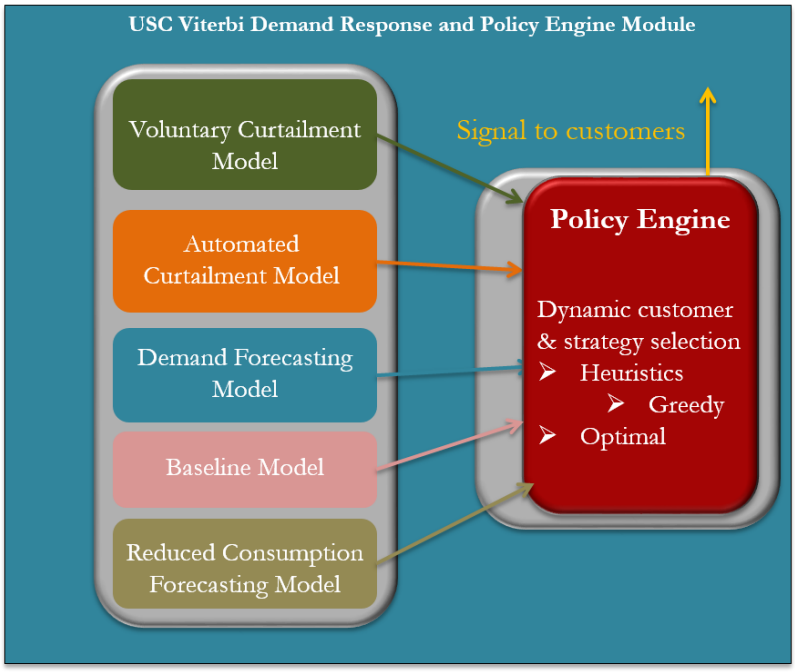


Figure 9: USC Policy Engine

The goal of the policy engine is to recommend a subset of customer, strategy pairs from an exponential number of available <customer, strategy> combinations. In addition, the policy engine was designed to dynamically adapt (Dynamic DR) to external events such as updated curtailment requirements or changes in the set of participating buildings. The inputs and output of the policy engine are shown in the above figure.

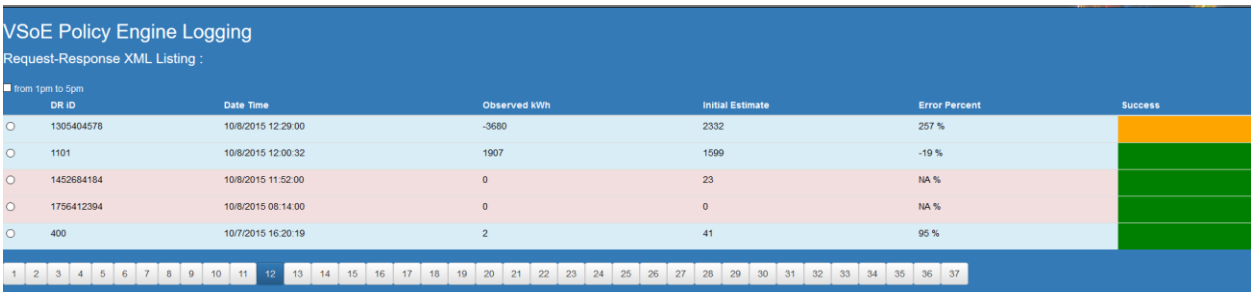


Figure 10: Error Before



Figure 11: Error After

The difference in error percent achieved by using the aforementioned methods in the Policy Engine are illustrated in the figures above.

Data Access & Loading into DRDR:

Data Access and ingest component is responsible for bringing data required for DDS training and prediction from outside data sources to one of the DRDRs in a timely manner. The scope this work includes (1) tools for accessing and loading bulk data in batch or changing data periodically within latency requirements into the DRDRs, and (2) writing data adapters to transform data representations to the DRDR database schema. There are three categories of data sources: external data, DWP data and SG Project data.

External data

The only external data source is current and forecasted weather data from NOAA that includes properties about max/min/average temperature, humidity, precipitation, cloud cover, and wind speed. This data had to be retrieved for different zip codes in the LA service area using the web service interface provided by NOAA. Weather data properties had to be accessed periodically – the periodicity determined based on the frequency with which the data is updated by NOAA. The properties had to then be stored in the DRDR.

DWP data

Data from other sources within DWP *(that are not already part of other DRDRs)* have to be accessed and stored within the DRDR periodically. These DWP data sources may be CIS, MDM and web portal. Some of these sources had to be bulk loaded once while others had to be accessed periodically (e.g. meter interval data). Some may also be bulk loaded at specific monthly intervals. Tools for scheduling and automation of these data accessed were developed. Adapters for transforming these data representations to the DRDR schema were developed. Some simple normalization or unit conversion of the data were required.

Project data

Data from the Smart Grid demonstration project is required by DDS. Most of these are already present within one or more of the DRDRs used by the project. However, those data required by DDS that are not present within the DRDRs have to be loaded into the DRDR for use by DDS. One example of this is survey data collected by the USC VSoE team. These survey data responses have to be exported from the external survey tool, translated to the DRDR schema and imported into the DRDR.

DRDR Database & Model Store

DRDR6 is the primary database used exclusively by the DDS for storing data used by it for training and prediction. Besides the input data being ingested, the DRDR6 also stores other persistent configuration information for default models, and details necessary for retraining models to reproduce historical forecasts. The database schema for the DRDR6 has to be defined. This includes defining data types for

columns and tables, relationship constraints between columns, and indexes. It also includes defining of database views, as required, over tables in DRDR6 and other DRDRs to support the querying for consumption and compliance training and prediction. The schema definition need to be tuned to meet the requirements of the queries and updates performed on the database, including bulk inserts/updates during ingest, and bulk queries for training.

The DRDR6 database or a co-located file system location also has to store consumption and compliance models that have been trained in the past for supporting future predictions in a manner consistent with the data present in the database.

Data Querying & Model Storage

This component is responsible for supporting queries over the DRDR databases and for creating *consistent* datasets that can be provided to the DDS library for performing training of and prediction using models. It is also responsible for storing and retrieving trained models and their associated configuration, such as feature sets, granularity, accuracy, and training data used.

Consistency refers to providing rows of data tuples that have the right set of columns (features used for training/prediction), for the right spatial and temporal granularity, and without any missing values. This requires performing data aggregation (to down sample datasets) and interpolation (to handle missing values). Both training data and prediction data have to use the same, consistent data aggregation and interpolation approaches.

Querying for training data results in large result sets from the database. So queries needed to be defined intelligently to cache prior query results in the filesystem and perform incremental queries. The latency requirements for performing the training determine the types of such performance optimizations required, if any.

Administrative Interface for Model Configuration, Training, Prediction & Selection

The admin interface is (a web browser interface) used by users to perform model training on-demand by users using features that are selected, for comparing the accuracy of predicted model results with observed values, for configuring the frequency and type of consumption and compliance models to be trained periodically as *standard* models, and to configure default models for use by the DDS web service.

On-demand model training & testing

This feature allows the user to select from a set of available consumption and compliance model algorithms available in the DDS Java kernel library and configuration parameters required for the model. It also allows the user to specify the necessary training features for the model, and the temporal (15min, 24hrs) and spatial (consumer groups) granularities. The model and training data specifications are used to call the DDS web service that then returns a *reference* to the trained model. This can then be used for subsequent predictions.

Comparison of accuracy of model results

This feature allows the user to predict the consumption or compliance for a specific time period, and temporal and spatial granularity using one or more model(s) that have already been trained, and optionally allows the predicted consumption/compliance values to be compared against observed values for the same time period and customers to return a CV-RMSE value of accuracy. This uses the DDS web service to perform the predictions and may directly use the DDS Data Access component to get the observed values of consumption and compliance for determining the accuracy.

Configuring standard models

The DDS web service allows predictions of consumption and compliance to be made using specific trained models or using default models that have already been trained. This feature allows the user to specify the model algorithms, configurations and training datasets that will be used to train consumption and compliance models periodically, on a schedule or when new datasets are available, and use these trained models as the default model for the DDS web service.

DDS Web Service Implementation

The DDS Web Service exposes four APIs and performs three tasks for each. The APIs provided correspond to those offered by the DDS Java kernel library and allows (1) Training of Consumption models, (2) Training of compliance models, (3) prediction of consumption given a model, and prediction of compliance given a model. The three tasks are querying for training or prediction data (for 1-4), model training and storage (for 1-2), and model prediction (for 3-4).

For training, the service has to retrieve a *consistent* training dataset for the given temporal and spatial granularities, time period and data features using the data querying component. This training data (stored as a file) and the model configuration parameters passed in the service call are used to invoke the DDS Java library that will return a trained Java consumption or compliance model object. The training time may occasionally take several hours, depending on the size of the training data set and model algorithm chosen. So the web service call may have to be asynchronous to avoid network timeout issues. The trained Java model, along with model configuration details (such as model algorithm, data features used, and granularity) should then be stored using the model storage component so that it can be used in future for making predictions.

For prediction, the service has to retrieve a trained model being used for prediction; this may either be a default model configured using the admin interface or a specific model referenced in the service call. The stored model configuration details and the given time periods and consumers are used to retrieve a *consistent* prediction dataset using the data querying component. The stored model is converted back to a DDS Java object and passed the prediction dataset and model configuration to return a set of predicted consumption or compliance values. These are then returned to the invoking client by the service.

Table 5: Data flow between Major Functional Components in DDS

Data Source	Data Destination	Description	Parameters	Notes/Constraints
DR Info Repos	DR Model Training	Feature Inputs for training consumption forecast models	Historical time series of customer demographics, address, # of household members, type of customer, Has EV or not, Enrolled in DR or not, Lat/Long of address, historical weather in zip code, Responding to curtailment or not, 15-min/hourly/daily KWh consumption	Training done once a day or once a week (depending on model) using data available till the end of previous day
DR Model Training	DR Info Repos	Trained consumption forecast model	Consumption Forecast Model file (binary)	Trained model updated and stored once a day or once a week (depending on model)
DR Info Repos	DR Consumption Forecast	Trained consumption forecast model	Consumption Forecast Model file (binary)	Requested once a day when a new trained model is available
DR Info Repos	DR Consumption Forecast	Feature inputs for consumption prediction	Current information on customer demographics, address, # of household members, type of customer, Has EV or not, Enrolled in DR or not, Lat/Long of address	Requested once every day
DR Info Repos	DR Consumption Forecast	Feature inputs for consumption prediction	Responding to curtailment or not, type of curtailment in progress	Requested every 15mins

Data Source	Data Destination	Description	Parameters	Notes/Constraints
DR Customer Selection	DR Consumption Forecast	Request for power consumption forecast in given region Response is a time series of customers and their future power consumption in that region	Feeder/substation, period of time in future Time series of customers and their future power consumption	Immediate request-response when curtailment required
DR Customer Selection	DR Curtailment Adaptation	Request for curtailment responsiveness of a set of customers in the past Response is the probability of responsiveness for those customers	List of customers, KWh reduction request, time of day, duration List of customers, probability of response	Immediate request-response when curtailment required
DR Info Repos	DR Curtailment Adaptation	DR curtailment for customers	List of customers, DR events sent to them, forecast and actual power consumption for them	Query on demand when curtailment required

Prediction with Partial Data

Applications in sustainability domains such as in energy, transportation, and natural resource and environment monitoring, increasingly use sensors for collecting data and sending it back to centrally-located processing nodes. While data can usually be collected by the sensors at a very high speed, in many cases, it cannot be sent back to central nodes at a frequency that is required for fast and real-time modeling and decision making. This may be due to physical limitations of the transmission networks, or due to consumers limiting frequent transmission of data from sensors located at their premises for security and privacy concerns. We propose a novel solution to the problem of making short term predictions in absence of real-time data from sensors. A key implication of our work is that by using real-time data from only a small subset of influential sensors, we are able to make predictions for all sensors. We evaluated our approach with a large real-world electricity consumption data collected from smart meters in Los Angeles and the results show that between prediction horizons of 2 to 8 hours, despite lack of real time data, our influence model outperforms the baseline model that uses real-time data. Also, when using partial real-time data from only ~7% influential smart meters, we witness prediction error increase by only ~0:5% over the baseline, thus demonstrating the usefulness of our method for practical scenarios. Low cost wireless sensors are increasingly being deployed in large numbers for performing monitoring and control in many sustainability domains such as in smart electric grids, transport networks, and natural resource and environment monitoring. These sensors are located at geographically dispersed locations and periodically send back acquired data to centrally-located processing nodes via wireless links and the Internet. They include sensors for monitoring natural resource and environment such as biodiversity and atmosphere; smart meters for measuring energy consumption; loop detectors installed under pavements for recording traffic; and meters on wind turbines that record wind speed and turbines' power output. Due to several factors, data from all sensors is not available at central nodes in real-time or at a frequency that is required for fast and real-time modeling and decision-making. For example, wind turbines record data every few seconds, but transmit data every five minutes to far-off research centers for use in forecasting algorithms. Physical limitations of existing transmission networks, such as latency, bandwidth and high energy consumption are key factors that limit the frequency of data transmission from sensors to central nodes. Sometimes, consumers may also limit frequent transmission of information from sensors located at their premises for security and privacy concerns. All these situations reflect the partial data problem, where only partial data from sensors is available in real time, and complete high resolution data become available only periodically, generally one or more times a day. Without addressing this problem, traditional solutions risk degradation in performance and inaccurate interpretation of generated insights. For instance, time series prediction methods are adversely affected by the prediction horizon length, and in the case of partial data, the effective prediction horizon for those sensors for which data is unavailable in real-time becomes larger, which in turn leads to detrimental increase in prediction error. Thus, the time series approach cannot be used for accurate predictions, for example, for up to 8 hours ahead. A possible approach is to develop creative solutions using data from a small subset of sensors selected on the basis of some heuristics or learning methods, while minimizing information loss resulting from leaving out data from remaining sensors. The intuition behind this approach is the fact that sensors located spatially close to each other or sensing activities driven by similar schedules - such as those on an academic campus or traffic on high density roads - are likely to be correlated. If this information can be leveraged, it will obviate the need for real time transmission from all sensors to the central nodes, and thereby reduce the load on the transmission network.

Also, it would make it simpler to add new sensors without straining the network. We distinguish partial data from missing data, which is arbitrary unavailability of data at random time periods due to diverse factors, whereas partial data is systematic unavailability of data for known time periods for a known

subset of smart meters, due to non-transmission of data in that period. While selective missing data is lost, partial data becomes available when batch transmission occurs, and can be used to re-train our models. We address the partial data problem in the context of smart electricity grids, where high volume electricity consumption data is collected by smart meters at consumer premises and securely transmitted back to the electric utility over wireless or broadband networks. There, they are used to predict electricity consumption and to initiate curtailment programs ahead of time by the utility to avoid potential supply-demand mismatch. Partial data problem arises when data from smart meters is only partially available in real-time. To address this, we propose a two-stage solution: first, we learn the dependencies among time series of different smart meters, then, we use data from a small subset of smart meters which are found to have high influence on others to make predictions for all meters. We leverage dependencies among time series sensor data for making short term predictions with partial real-time data. While time series dependencies have been used previously, the novelty of our work is in extending the notion of dependencies to discover influential sensors and using real time data only from them to do predictions for all sensors. Using real-world electricity consumption data, we demonstrate that despite lack of real time data, our prediction models perform comparably to the baseline model that uses real-time data, thus indicating their usefulness for practical sustainability domain scenarios.

Accurate and Efficient Selection of the Best Consumption Prediction Method

Smart grids are becoming popular with the advent of sophisticated smart meters. They allow utilities to optimize energy consumption during peak hours by applying various demand response techniques including voluntary curtailment, direct control and price incentives. To sustain the curtailment over long periods of time of up to several hours utilities need to make fast and accurate consumption predictions on a large set of customers based on a continuous flow of real time data and huge historical data sets. Given the numerous consumption patterns customers exhibit, different prediction methods need to be used to reduce the prediction error. The straightforward approach of testing each customer against every method is unfeasible in this large volume and high velocity environment. To this aim, we propose a neural network based approach for automatically selecting the best prediction method per customer by relying only on a small subset of customers. We also introduce two historical averaging methods for consumption prediction that take advantage of the variability of the data and continuously update the results based on a sliding window technique. We show that once trained, the proposed neural network does not require frequent retraining, ensuring its applicability in online scenarios such as the sustainable demand response.

Time Series Clustering

The proposed methodology for usage based segmentation consists of the following stages that are performed daily. The assumption is that this operation is performed at midnight of day *d* for the task of predicting consumption between 1-5pm on day *d*:

1) Perform a simple normalization by decomposing the daily electricity consumption time series (i.e., 96 values at a 15-minute granularity per meter). Specifically, given a daily consumption profile *l(t)*, we decompose it as *l(t) = as(t)*, where $a = \sum_{t=1}^{96} l(t)$, and $s(t) = \frac{l(t)}{a}$. a represents the daily total consumption and s(t) is the normalized time-series.

2) The second stage clusters the normalized time series across the population. Specifically, every time-series $s_n^d(t)$ for day *d* and meter *n* in the dataset is mapped to the closest center C_i^d that minimizes the squared error$E(s, C_i) = \sum_{t=1}^{96}(C_i(t) - s(t))^2$. Finding representative centers that minimize the sum of the mean squared errors over all time-series for day *d* is a standard clustering problem. We solved this problem using the K-means algorithm, a popular statistical clustering approach. Algorithm 1 summarizes the main steps of the proposed approach.

    a. The classic K-means algorithm needs the number of clusters, *K*, to be known a-priory. In order to decide a proper value for K, considering the large number of potential candidate for representative time-series "shapes", we used the Dunn's index. Similar to other indices, the aim is to identify sets of clusters that are compact, with a small variance between members of the cluster, and well separated, where the means of different clusters are sufficiently far apart, as compared to the within cluster variance. The reason for choosing this evaluation metric is that there is no ground truth about the number of clusters. Specifically, unlike other metrics, Dunn's index is an internal evaluation scheme, where the result is based on the clustered data itself.

Algorithm 1. Proposed Clustering Algorithm based on K-means
Require: Daily time-series $s_n^d(t)$ for all meters n ϵ N, min and max number of clusters *for k ϵ [min number of clusters, max number of clusters]* *run K-means* *calculate Dunn's Index* *if the Dunn's Index for this configuration is minimum* *return the clustering results and K = k* *end* *end*

3) The third step is to train a forecasting model per cluster to improve the prediction error as compared to a model that is trained on the complete population. For this task, we took a data driven approach consisting of obtaining a functional model that relates the value of the response variable $s_n^d(t)$ with the values of predictor variables $s_n^d(t-2), s_n^d(t-1)$. Other features can be explored. Specifically, we use a regression tree as a predictive model which maps predictor variables $s_n^d(t-2), s_n^d(t-1)$ to $s_n^d(t)$. A regression tree is "learned" by splitting the source dataset into subsets based on an attribute value test. This process is repeated on each derived subset in a recursive manner called recursive partitioning. The recursion is completed when the subset at a node has all the same value of the target variable, or when splitting no longer adds value to the predictions. Finally, a simple regression model is fit

to the small data that belong under each node. We perform this process independently for each cluster; a regression tree is thus learned for each cluster.

4) The last step is to perform predictions for each time-series $s_n^d(t)$ for day d. Recall that the objective of learning a regression tree is to learn a model for predicting the response $s_n^d(t)$ with the values of predictor variables $s_n^d(t-2), s_n^d(t-1)$. Given a forecast or availability of observed values for $s_n^d(t-2), s_n^d(t-1)$ we can predict the response $s_n^d(t)$.

Evaluation

A. Dataset Description: We evaluated our proposed approach using a dataset of 39 MV90 customers. The dataset contains the electricity consumption values at every 15 mins from 5/30/2012 00:15 to 12/17/2013 0:00. The normalized load shapes for day 1 are shown in Fig. 12 below.

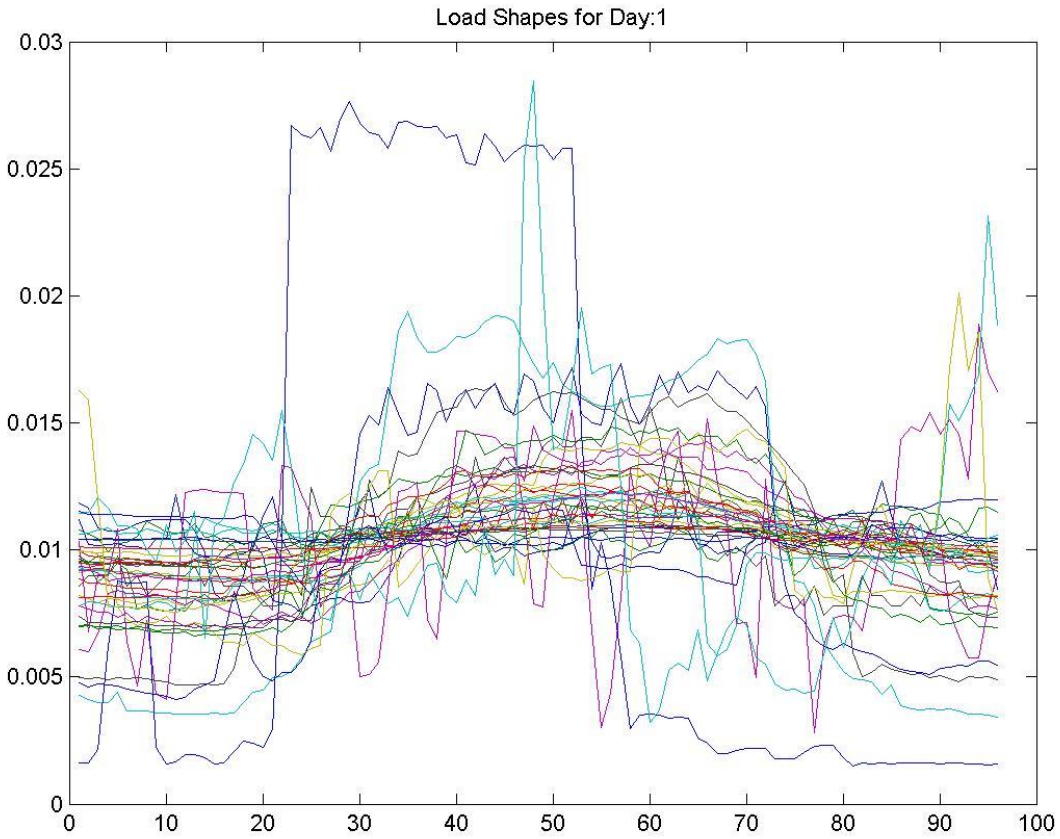


Fig. 12. Normalized Load Shapes of MV90 customers for day 1 in our dataset.

B. Clustering Quality: The result of the clustering step for day 1 is shown in Fig. 13. Evidently, the time-series are very well separated into five groups. We repeated this visual validation for 10 days and confirm the quality of the clustering in all cases.

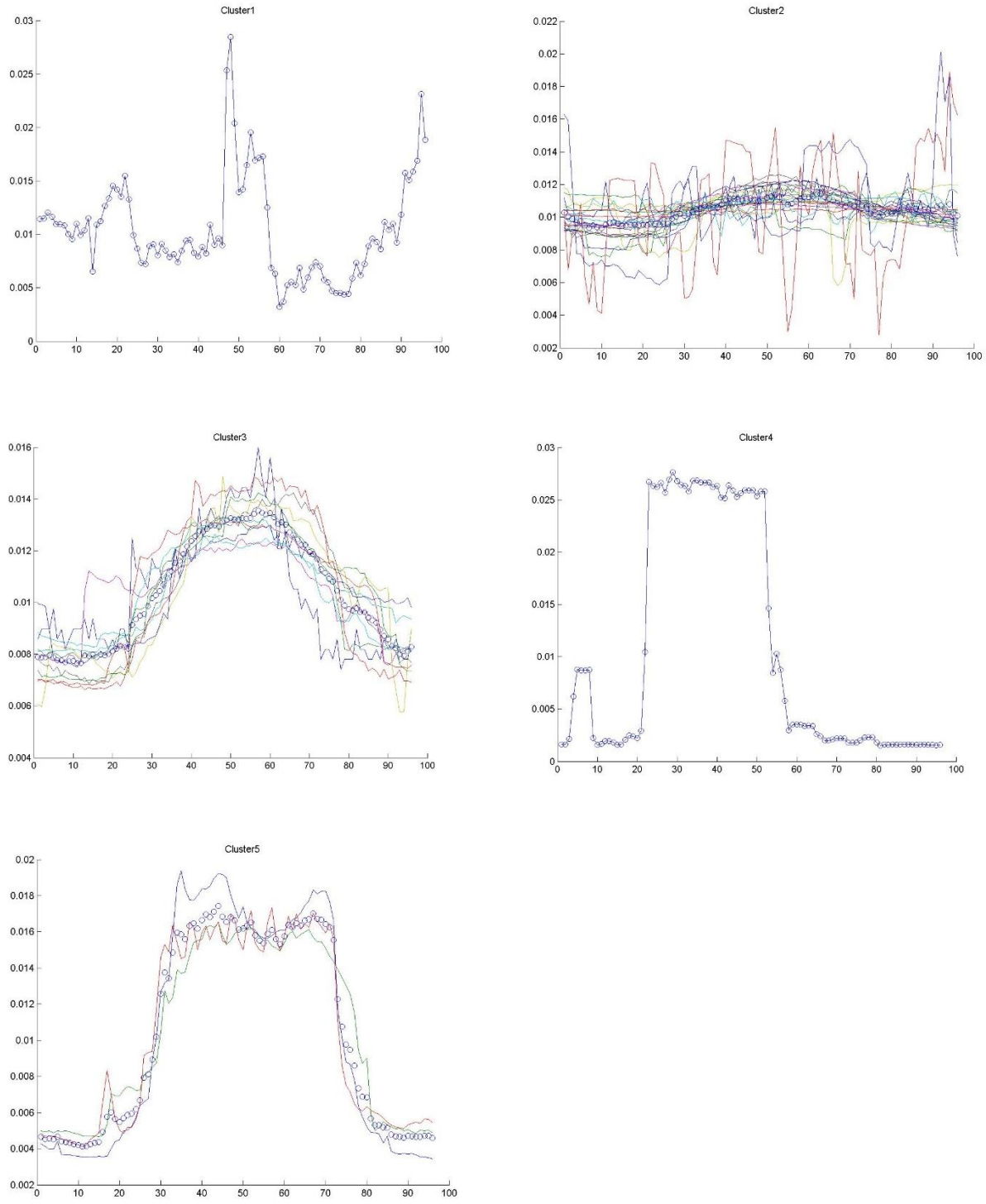


Fig. 13. Result of clustering MV90 time-series for day 1.

We further examined the robustness of the clustering by evaluating the stability of the time-series data segmentation across 368 days. Fig. 14 shows the result. Evidently, the clustering configuration remains fairly stable throughout the entire time period. In fact, by averaging out the participation of customers

to the same cluster on each day and counting the number of times they belong to the same group, it can be shown (Fig. 15) that the clustering configuration can be considered stable for practical purposes. In case, to account for variability in electricity consumption across days, we suggest performing this clustering on a daily basis for the most up to date customer segmentation.

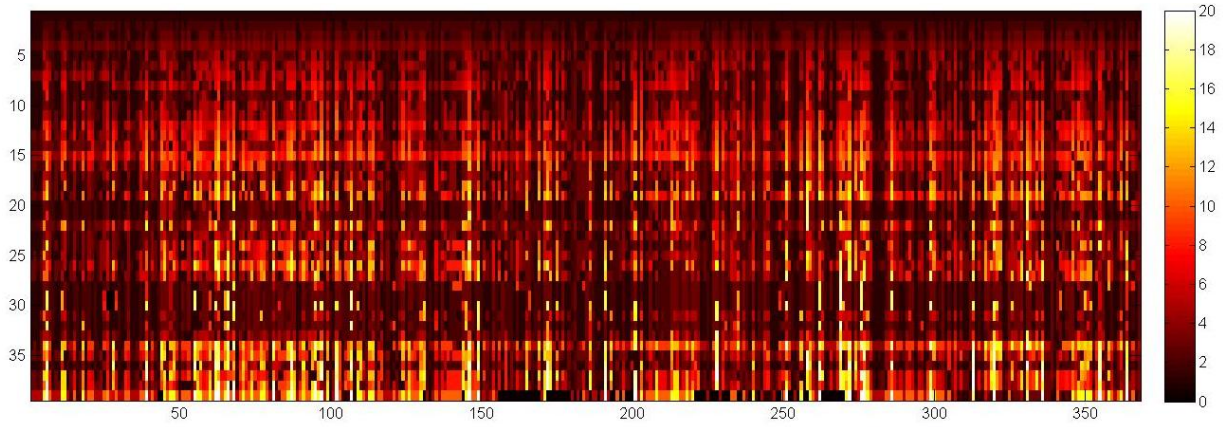


Fig. 14. Clustering result of MV90 customers for 368 days in our dataset. X-axis represents days. Y-axis represents customers. Colors denote cluster id.

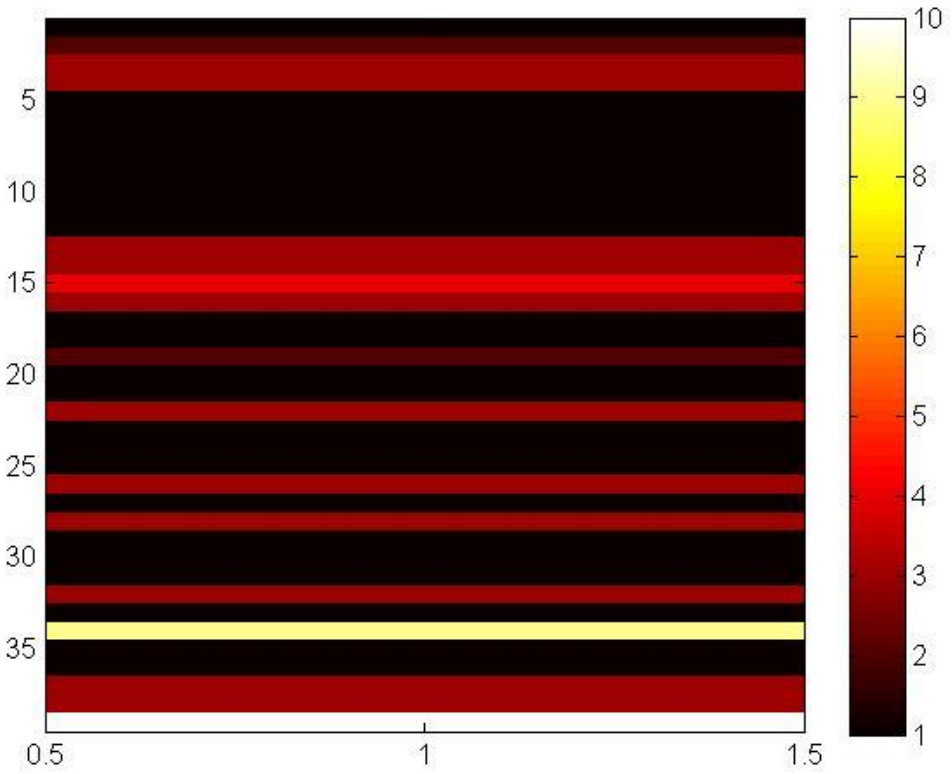


Fig. 15. Average clustering configuration of MV90 customers over the course of 368 days. X-axis represents days. Y-axis represents customers. Colors denote cluster id.

Prediction Accuracy Improvement: We evaluated the performance of our proposed approach compared to a naïve regression tree based approach that learns a tree from all data. Both methods were trained using data from day *d-1* and were tasked to predict the values of each individual time-series for day d between 1-5pm. We computed MAPE per day for 368 days by aggregating all individual errors. Fig. 16 shows the results. Even though RegTree(All) achieves good performance overall, i.e., less than 10% error for the majority of days, the proposed approach (RegTree(per cluster)) that learns multiple regression trees, one per customer group, achieves effectively zero error. This is a significant improvement compared to the previous approach.

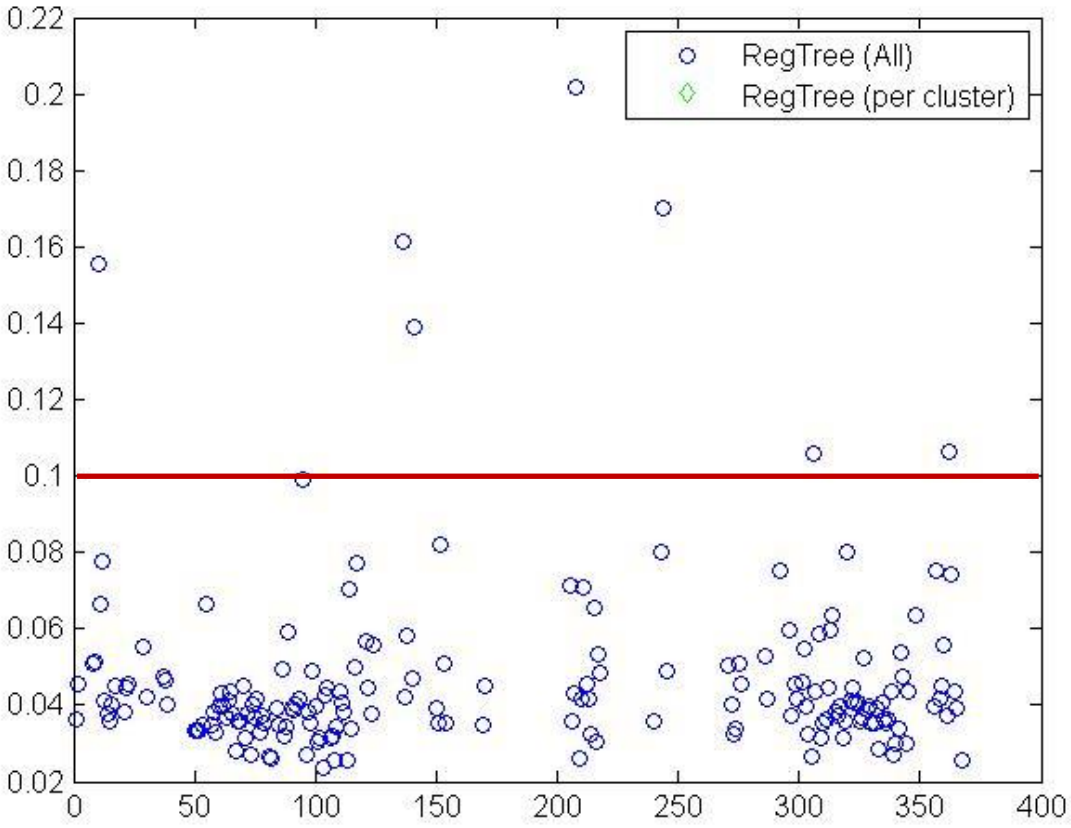


Fig. 16. Comparison of prediction error for day 1 between a regression tree learned across the whole population (i.e., RegTree(ALL)) and the proposed method (i.e., RegTree(per Cluster)).

Semantic Information Modeling and Integration for DR

The USC VSoE team developed an integrated Smart Grid information model using Semantic Web techniques for dynamic DR.

Smart Grid being diverse in nature involves a wide range of concepts from various domains. It is not possible to build one single model from scratch which encapsulates all the relevant concepts. Hence, the developed solution included identifying well defined and understood ontologies in the candidate domains and integrating these by filling in the gaps. This modular and extensible strategy leverages the features provided by Semantic Web technologies, allowing to build on top of domain expertise, and providing familiar conceptual terms for users. Specifically, the USC VSoE team identified common or related concepts across domains and introduced relationships between them, introduced new, relevant concepts that were missing from a domain ontology, mapped existing metadata schemas to an ontology framework, and constructed new domain ontologies. The final result, a Smart Grid information model, is represented using Web Ontology Language (OWL). It consists of the following component ontologies:

- **Electrical Equipment Ontology:** The International Electrotechnical Commission's Common Information Model (CIM) is a standard that describes the components of a power system at a distribution level and defines information exchange between them. CIM describes Equipment at the Consumer side and how much consumption the equipment records at each point in time in a structural form but does not describe their semantics. Hence, the USC VSoE team transformed the CIM standard to an ontology representation.
- **Organization Ontology:** To differentiate between types of organizations (e.g. airline or university) whose electricity consumption might differ, terms from the DBPedia Ontology have been reused.
- **Infrastructure Ontology:** The Smart Grid information model captures environment concepts including transportation networks, buildings and so on, besides the Power Grid infrastructure in an effort to improve demand response applications by bringing in context about the type of infrastructure which consumes electricity.
- **Weather Ontology:** Weather information is helpful in understanding the electricity consumption pattern in a particular geography. The NNEW Weather Ontology which uses SWEET 2.0, JMBL, and WordNet Ontologies in a coherent manner was integrated to provide a rich set of vocabularies to define various weather phenomenon. The SWEET Ontology captures concepts pertaining to earth sciences like Physical Phenomenon, Space, Human Activities etc., whereas WordNet provides large set of domain independent lexical database. NNEW Ontology makes an attempt to reuse the concepts mentioned in other ontologies and carefully extend those concepts which are essential to describe weather phenomenon.
- **Spatial Ontology:** Power consumption is linked to specific equipment or infrastructure at a spatial location drawing power from feeders supplying at that location. But the usage is also influenced by people whose locations change or external influences like weather that have regional impact. The fact that a building is part of a city's downtown gives an intuition that the building will experience decrease in demand during evening and during weekends. Beyond

latitude and longitude, address or zip codes may be available. Just like organizational and infrastructure concepts the spatial concepts are also covered in the DBPedia Ontology, and the fact that some of the basic relationships amongst them are already established makes it a much better choice compared to other isolated ontologies.

- Temporal Ontology: Power consumption happens over time, and demand response applications specifically attempt to learn from past consumption patterns to predict and control future consumption. Scheduling information of infrastructure, electrical equipments as well as of individual people are relevant in understanding how much the electricity demand is going to be. The W3C calendar Ontology provides the set of vocabularies to capture scheduling and calendering related information. The Ontology is an attempt to integrate ICalendar, a widely used format for sending meeting requests, data with other Semantic Web data.

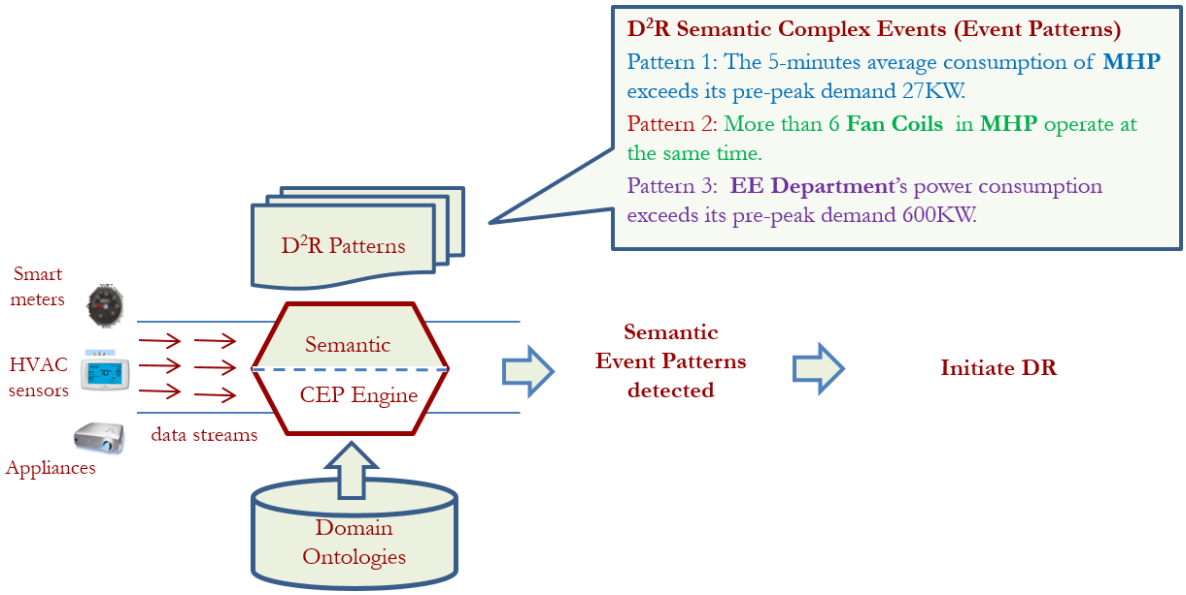
The ontologies were integrated using Protege and the instances were populated using Jena Semantic Web Framework for Java. The Ontology schema as well as the instance data were stored in MySQL Database using Jena API.

Semantic Complex Event Processing

Emerging Big Data applications in areas like e-commerce and energy industry require both online and on-demand queries to be performed over vast and fast data arriving as streams. These present novel challenges to Big Data management systems. Complex Event Processing (CEP) is recognized as a high performance online query scheme which in particular deals with the velocity aspect of the 3-V's of Big Data. However, traditional CEP systems do not consider data variety and lack the capability to embed ad hoc queries over the volume of data streams. We have developed H2O, a stateful complex event processing framework, to support hybrid online and on-demand queries over real-time data. We have proposed a semantically enriched event and query model to address data variety. A formal query algebra has been developed to precisely capture the stateful and containment semantics of online and on-demand queries. We describe techniques to achieve the interactive query processing over real-time data featured by efficient online querying, dynamic stream data persistence and on-demand access.

Existing Big Data solutions primarily focus on addressing the volume aspect of the 3-V's of Big Data [16]. As a result, specialized technologies including distributed databases, Hadoop and NoSQL have been developed to support scalable data storage and on-demand querying over large volumes of data. These systems usually provide high read performance for data that has been persisted and properly indexed. Recently, the velocity and variety sides of Big Data are attracting increasing attention. Organizations such as social media, utility companies and financial institutions often face scenarios where they need to analyze heterogeneous "in-flight" data for businesses analytics. For example, applications including real-time bidding (RTB), digital shopping, dynamic demand response in Smart Grid and algorithmic trading need to process real-time data such as advertisements, shopping activities, sensor readings and stock ticks, respectively, originating from various sources to make timely decisions. Data for these applications arrive at high-rate streams and may vary in terms of structure and meanings. One challenge of these emerging real-time Big Data applications is the need to concurrently support both online and on-demand queries over data streams. Online queries represent persistent user interests that need to be

evaluated continuously as new data appears in order to trigger real-time actions. On the other hand, on-demand queries model transient user interests which need to be answered in an ad hoc manner, usually using stored history data. Traditional Big Data solutions often adopt a “multi-temperature” architecture where data that is frequently accessed (hot data) is on fast storage compared to less-frequently accessed data (warm and cold data) placed on slower storage. Real-time data appears at the top of hot storage requiring on-the-fly write and read processing. The unique characteristics of real-time data offers the opportunity for on-the-fly querying with dynamic data life-cycle management that obviates the need to persistently store everything. One key notion of real-time data is its transient property: (1) new data arrives on streams at high velocity; and (2) old data leaves streams or the values of data fade away at potentially high velocity. For example, consider a digital shopping scenario where a large number of web orders are placed and processed concurrently. Activities such as order creation, payment and delivery need to be monitored continuously to detect service level agreement (SLA) violations and offer on-demand status check. However after an order is completely fulfilled, it is no longer “alive” or of value for SLA detection and status check queries. Complex Event Processing (CEP) is a popular technique for querying real-time data. CEP deals with detecting real-time situations, represented as event patterns, from among many event streams. CEP is commonly used for operational intelligence, where online query pattern detection drives real-time responses, and is used in domains overlapping with Big Data applications, ranging from e-commerce to energy industry to financial services. However, traditional CEP systems do not consider data variety and only support online queries. Most existing CEP systems such adopt a SQL-like query language and evaluate event data at the syntactic level. These CEP queries are pre-defined, listen to new events and trigger outputs when the patterns are matched completely. Temporary states observed by the system are not managed for external access and hence not available for on-demand querying. In this paper, we propose H2O, a stateful Complex Event Processing framework to support hybrid online and on-demand querying over real-time data. We introduce a unified event and query model for online and on-demand query specification over heterogeneous real-time data streams. We developed a formal query algebra to capture the stateful and containment semantics of queries, which forms the basis for dynamic life-cycle management and on-demand access of real-time data.



Cloud-Based Software Platform for Big Data Analytics in Smart Grids

Scientific work flows and data flows provide a convenient abstraction for composing data transformation pipelines and in silico experiments using interconnected building-block tasks. These are then run on local workstations or remote cyberinfrastructures using workflow engines that orchestrate task executions and the data exchanges between them. Despite their growing popularity and ease of use, existing workflow engines have limited support for processing continuous data streams with the same flexibility and efficiency as processing files. Support for both bulk data files and dynamic streaming data, which scales to thousands of sensor streams with low latency processing, is essential for composing data acquisition pipelines for the Smart Grid CPS. Further, when running in an operational setting, these pipelines are in an "always on" mode. Hence, any change to the pipeline's composition must be done in-place, without loss of in-flight data. This form of application dynamism is, again, not considered by contemporary workflow systems.

As a solution, we developed the Floe data-flow framework. Floe offers novel data abstractions for composing hybrid data flows that include file and stream processing and is designed to operate continuously. Users' data flows are designed as task graphs whose nodes are the application logic, or *pellets*; the directed edges represent data transferred between them. Floe supports cycles and uses decentralized orchestration. Data is directly exchanged between pellets, without a central coordinator, to reduce the message/file transfer latency. The framework manages pellet-to-pellet message channels and triggers pellet execution. Pellets can iterate over incoming messages or have messages pushed to them. Data parallelism is intrinsic; users simply flag pellets to operate sequentially or concurrently on incoming messages.

Floe is designed from the ground-up to operate in commodity cluster environments and on IaaS clouds, with support for cloud providers such as Eucalyptus, Amazon Web Services (AWS), and Windows Azure. The framework can implicitly scale-out and scale-in on elastic cloud virtual machines (VMs) based on current processing needs. It also supports multicore processing, and can scale-up and scale-down the number of cores used within a VM. The manager acquires and releases VM instances from the cloud

service provider currently configured. Individual pellets have exclusive use of one or more CPU cores on a VM, and pellets are sandboxed from each other using Java 7's ForkJoinPool. The framework can dynamically change a pellet's core allocation at runtime to meet user-specified quality of service (QoS) metrics such as message latency time or CPU usage thresholds. For data-parallel pellets, the framework can tune the concurrency level by increasing the thread parallelism. These optimizations are automatic and transparent to users.

Conceptually, the USC Cloud-Based Software Platform for Big Data Analytics in Smart Grids is shown below:

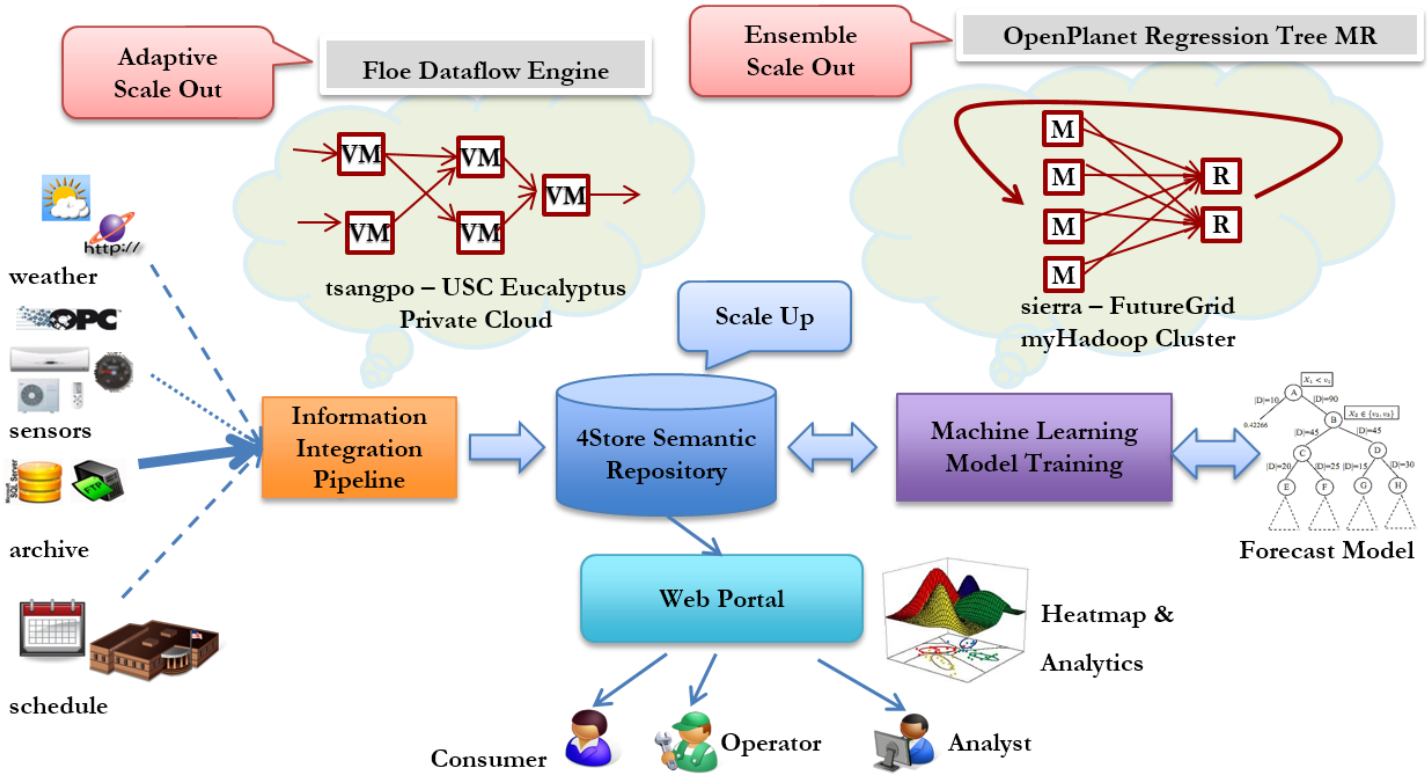


Figure 17: USC Cloud-enabled Software Architecture for DR

Secure Cloud-based Data Repository and Privacy

Cloud storage has become immensely popular for maintaining synchronized copies of files and for sharing documents with collaborators. However, there is heightened concern about the security and privacy of Cloud-hosted data due to the shared infrastructure model and an implicit trust in the service providers. Emerging needs of secure data storage and sharing for domains like Smart Power Grids, which deal with sensitive consumer data, require the persistence and availability of Cloud storage but with client-controlled security and encryption, low key management overhead, and minimal performance costs. Cryptonite is a secure Cloud storage repository that addresses these requirements using a StrongBox model for shared key management. Our experiments show that Cryptonite clients achieve a 40% improvement in file upload bandwidth over plaintext storage using the Azure Storage Client API despite the added security benefits, while our file download performance is 5 times faster than the baseline for files greater than 100MB.

Cloud computing has gained immense following in the business and scientific communities due to the ease of access and management, combined with a pay-as-you-go model for elastic on-demand resource usage. Of the diverse Cloud service offerings, Cloud storage is by far the more popular, whether used as an IaaS like file or BLOB store, PaaS like SQL Azure or SaaS like DropBox. These storage services are used for online content distribution, synchronization across devices, and for document sharing by enterprises and scientific collaborations.

Despite its success, there is heightened concern about the security and privacy of Cloud-hosted data to many eBusiness and eSciences that are considering shifting to Clouds. These arise from reasons: shared Cloud infrastructure for storing data from different organizations, co-location of multi-tenant applications with the storage services, and malicious insiders at Cloud providers getting access to data.

These do not presuppose ill-intentions by Cloud providers, who make a best effort (but not guarantees) of data security, but are rather the consequence of the “shared infrastructure managed by third party providers” model of Clouds.

Existing Cloud storage services only provide basic access control mechanisms 2 , and the limited research on secure, shared Cloud repositories often require extensive deployment of infrastructure services that undermines their manageability. Specifically, there are two classes of current solutions. One uses simple file en/decryption on the client side, managed through shared keys, such that only encrypted files are hosted in Clouds. While this works for a small number of files and users, key sharing and management becomes unsustainable as the number of users sharing data grows. A second solution is to allow the Cloud providers or a third-party offer more advanced security services and manage user credentials such as Dropbox. However, this approach still “trusts” an external service provider to secure their plaintext data. Consider the following scenario to motivate our work.

Smart Power Grids are giving utilities unprecedented access to real-time power consumption data on individual customers. Managing and analyzing this data requires large-scale compute and storage resources such as offered by Clouds. As part of the Los Angeles Smart Grid Demonstration project, the University of Southern California (USC) campus is serving as a testbed to research Smart Grid software technologies and human behavior to study power usage. This multi-disciplinary research has several departments and researchers involved, and data is collected on buildings, occupants, campus events, classroom schedules, and weather, in addition to Smart Meter and sensor data. Research regulations require that the different owners of this shared dataset – including the campus power consumers, who number in the thousands – have final control on which research groups have access to their datasets.

A Cloud-hosted data repository to hold personally identifiable information for scientific and operational needs should enforce this single owner/multiple writers/multiple readers' permission on individual data files with low management overhead, while ensuring that plaintext data is not stored in the Cloud.

This motivates the need for a data storage service which retains the persistence and availability offered by public Cloud storage but with security and encryption that is controlled by the clients, a low key management overhead, and compatibility with existing storage service interfaces while not sacrificing performance and scalability.

Cryptonite is a secure Cloud storage repository that addresses these requirements. Our design introduced earlier is validated here, to wit we present an implementation of the Cryptonite service and desktop client on the Microsoft Windows Azure Cloud platform. We also discuss optimizations to overcome data security overheads and provide an empirical analysis of the improvements.

We implemented Cryptonite, a secure data repository that runs within Azure and provides service APIs compatible with existing Cloud storage services. We presented pipelined and data parallel performance optimizations to reduce the security overhead caused through encryption and key management, and we experimentally evaluated Cryptonite on the Azure Cloud, compare it with baseline client storage access, and demonstrated the efficacy of our optimizations.

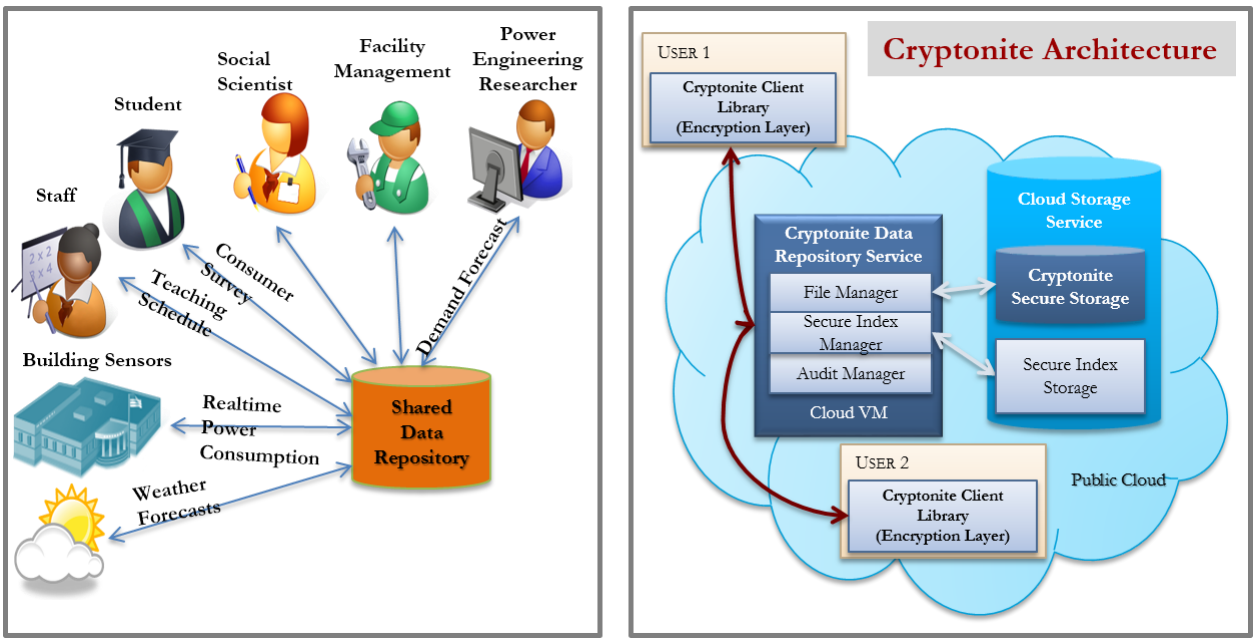


Figure 18: Shared Data Repository / Cryptonite Architecture

Customer selection and curtailment strategy

One of the problems solved in this demonstration is selection of customers and curtailment strategies they should adopt to achieve the targeted curtailment value. The USC VSoE team developed several building selection algorithms for the facility operator to pick and choose from as per the requirements, i.e., real-time adaptability to unexpected peak demand or situations where adaptation during a DR event is needed (dynamic DR) to sustain a consistent power reduction.

To address this problem, the USC VSoE team defined the concept of sustainable DR as a DR event that can achieve consistent load reduction for the scheduled time frame. The objective of sustainable DR is to maintain reduction as much stable as possible for the DR event duration, as shown in the Figure below.

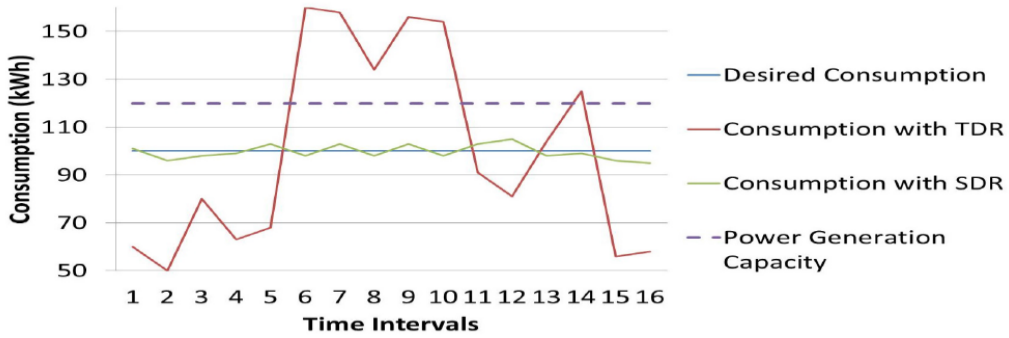


Figure 19: Sustainable Demand Response

The USC VSoE team developed heuristics for the computationally efficient selection of the right customers and strategies to achieve the desired curtailment during a DR event. Despite the good

performance of these methods (average observed error of less than 3%), curtailment errors are unbounded and could be as high as 70% in extreme cases. To address this limitation, the USC VSoE team subsequently developed an effective customer selection algorithm that can minimize the curtailment error, i.e., the difference between the requested and achieved curtailment values. The solution provided is integer linear programming formulation which can handle the challenges of scalability, fairness and adaptability for optimally selecting customers and curtailment strategies that minimize the curtailment error during DR events. Experiments on data obtained from the USC campus microgrid have validates that this new algorithm can achieve near exact curtailment values with almost zero error (error is in the range of 10^{-7} to 10^{-5}). To address the challenge of the scalability of ILPs, we developed several heuristics and approximate algorithms with bounded curtailment errors which trade-off accuracy with speed.

Curtailment Estimation

Accurate estimation and evaluation of consumption reduction achieved by participants during Demand Response is critical to Smart Grids. For example, estimated baseline consumption is overlaid in the sample profile of observed electric consumption during DR for a USC building in the Figure below. The difference between baseline predictions and actual consumption is positive in all cases, indicating that consumption shedding was achieved during the DR event. The Figure to the right demonstrates a more complicated scenario. In this case, observed consumption during the DR period does not exhibit a sharp drop as before. Instead, it fluctuates during the DR event window, and exhibits a decrease afterwards. This leads to negative kWh difference between most baseline predictions and actual consumption. This means that a bad baseline consumption assessment can result in misinterpretation of consumption reduction estimation and evaluation due to DR.

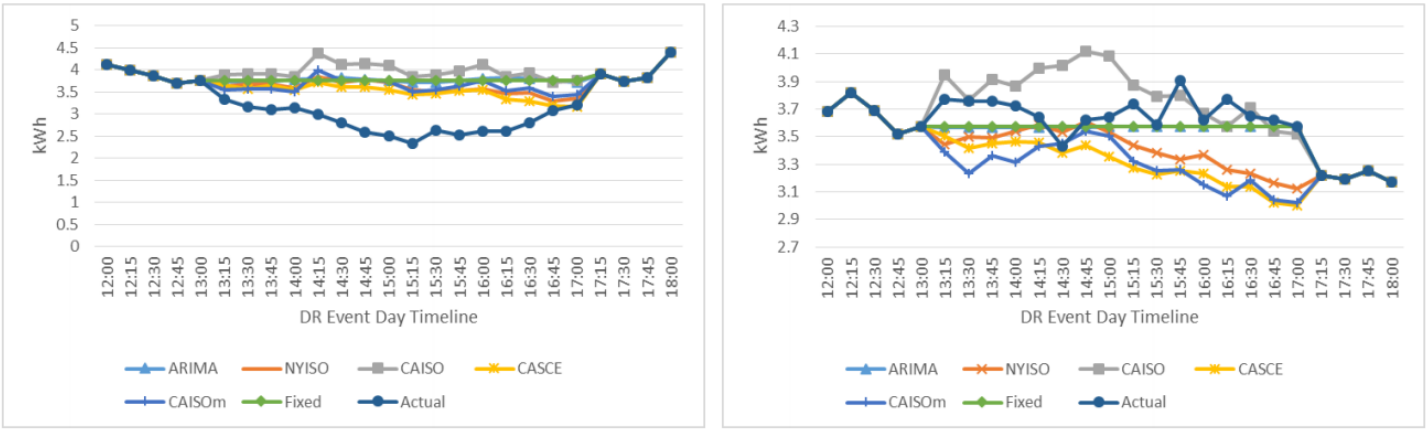


Figure 20: Dependence of estimated electricity consumption shedding on accurate baseline consumption forecasting

The USC VSoE team performed an in-depth study of popular estimation methods used to determine the extent of consumption shedding during DR using real-world data from the USC campus microgrid and showed that choosing a good baseline depends on both intrinsic (e.g., DR strategy, day of week) and extrinsic (e.g., temperature, human behavior) factors. Since it was found that the amount of computed curtailment (i.e., area between observed reduced consumption and baseline) depends on the accuracy

of the baseline model used and that different baseline models can result in different curtailment estimates, the USC VSoE team developed novel machine learning methods to directly predict reduced consumption during DR. Estimates of reduced consumption are used by the USC policy engine for optimal customer selection during the planning phase of a DR event.

Partial Real-time Data Availability:

While smart meters can collect data at a very high speed, in many cases, such data cannot be sent back to LADWP at a frequency that is required for fast and real-time modeling and decision making. This may be due to physical limitations of the transmission networks, or due to consumers limiting frequent transmission of data from sensors located at their premises for security and privacy concerns. To address this challenge, the USC VSoE team has developed a novel solution to the problem of making short term predictions in absence of real-time data from sensors. By using real-time data from only a small subset of influential sensors, the USC VSoE team has been able to make accurate predictions for all sensors in real-time. Specifically, when using partial real-time data from only 7% of the smart meters, the USC has demonstrated only a slight prediction error increase (less than 0.5%) over the baseline that had access to data for all sensors in real-time.

Customer segmentation

The large amount of high speed data coming from smart meters and other smart appliances such as thermostats, luminosity sensors, etc., pose significant challenges to real-time data processing and decision making by impacting the efficiency and speed at which information can be extracted from data streams. Traditional solutions for predicting energy consumption and curtailment analyze either individual or groups of customers by applying prediction techniques on the historical energy consumption time series. Individual customer predictions are challenging because different prediction methods give different results in terms of accuracy for distinct consumption trends. Predicting consumption for each customer can become a computational bottleneck especially for large smart grids with millions of customers. i.e., the response time for consumer data processing is on the order of a few hours. Clearly, such performance guarantees are inefficient for dynamic DR. In this regard, clustering techniques have the advantage of making predictions easier by reducing the noise in the aggregate customer energy consumption time series, and reducing the customer prediction time complexity by not being required to running prediction algorithms on individual customers. A good customer clustering can provide utilities with an optimal set of customers to target during dynamic DR. The USC VSoE team has developed novel methods for the continuous clustering of consumption time-series data that are streaming from a massive number of smart sensors (e.g., 52,000 meters in LADWP). The advantage of the proposed approaches is three-fold. First, clustering can be performed incrementally on “data-in-motion”, i.e., new data points can be incrementally integrated as they arrive in a stream allowing the clustering configuration to be computed once and updated incrementally with the arrival of new observations. Second, by co-integrating customers’ consumption values in a vector it is possible for emerging patterns to be mined. Third, it becomes possible to form groups of customers or smart meters across time for efficient training (i.e., with respect to computation time) and improved prediction accuracy of the developed machine learning models.

Demonstration challenges

There are several challenges which made this demonstration complex and the solution unique. These challenges are:

- Continuous batch information ingest for analytics and diffusion.
- Provide data storage security, owner-controlled data sharing, data integrity and audit, assured file deletion and secure search.
- Detect semantic event patterns in real time that necessitate DR
- Predict curtailment and reduced consumption during DR
- Customer segmentation for enhanced prediction accuracy based on consumption and behavior patterns.
- Predict consumption in the absence of real time data from sensors.
- Develop scalable solutions that are compatible with other software infrastructure for easy integration.

DR prediction accuracy tests:

Several tests have been performed to determine the accuracy of developed technology. The table below summarizes the results of one such test that was performed in the 2014 demonstration period.

Table 6: DR Tests for determining accuracy

Method for computing baseline	Southern California Edison (SCE) with adjustment factor based on data from 9AM-12PM the day of the DR event (assumed between 1-5PM)
Number of considered buildings*	11/40
Methodology	Test one building with one strategy for an entire hour
Total number of tests (buildings x strategies)	20

*Many buildings have been eliminated due to various reasons: real-time data not recorded, building not ready for experiments, fixed meter readings throughout the day. The table above lists the buildings considered for testing (check performed on June 24, 2014 and then again in July 16, 2014)

After testing several buildings, a list of buildings with accuracy testing is available. Not all available strategies have been tested for those buildings. The USC VSoE team has been selecting only those building-strategy pairs that had a positive curtailment estimate. The observations concluded that:

Buildings that will presumably give good accuracy: (1) GFS, HSH, KAP; (2) ASC, DRB; (3) OHE, SCB.

Buildings not recommended for DR: ALM, BKS.

Inconclusive buildings: STU, TCC.

Notes on observed vs. estimated values from the Table Above:

GFS all strategies – consumption increases drastically during 1-5PM (from around 190kW to 400kW) maybe due to a chiller going online. Because of the morning adjustment factor the baseline will be lower than the actual consumption causing the observed to be negative. DR events may not be suited to start immediately at 1PM for this building.

KAP strategy 2, **OHE strategy 4**, **SCB strategy 4**, **SCB strategy 2**, **STU strategy 2** - observed is 0 kWh due to non-numerical values in the real-time data (7/8/14 and 7/10/14). A software patch to handle these values is under development.

Historical data analysis:

1- Estimated kWh:

The inaccuracy of the baseline was determined to be caused by the lack of historical data. The USC VSoE team has analyzed data between July 17, 2012 and July 17, 2014. A total of 34 buildings have days with incomplete data totaling 1,949 days of 24,820 possible, or 7.85% of the total data. Of these 399 are in 2012 the rest being in 2013 and 2014. It can be seen that the days with missing data are distributed across buildings. 12 buildings have more than 50 incomplete days each.

The USC VSoE team have considered any day with one or more 15 minute intervals missing. Some day's exhibit large gaps while others are completely missing for some of the buildings. These large gaps in the data sets cause the past 10 days used by the Southern California Edison baseline to be far apart. Our algorithm skips any day with missing values. Therefore, the distribution of the days with missing data is equally important because if they are clustered together the days used by the ISO baseline can be spread across months. Interpolating missing data is not a viable option as the large gaps will likely produce wrong estimates.

While the large gaps do not occur frequently for the latest data after June 2014 their presence in the older datasets impacts the accuracy of the curtailment estimates used in predicting future curtailment.

Furthermore, the inaccuracy is also due to the averaging curtailment model in use. The model relies on historical DR events and since these are spread across the year its accuracy declines. Ideally enough DR events for each building should exist for each season.

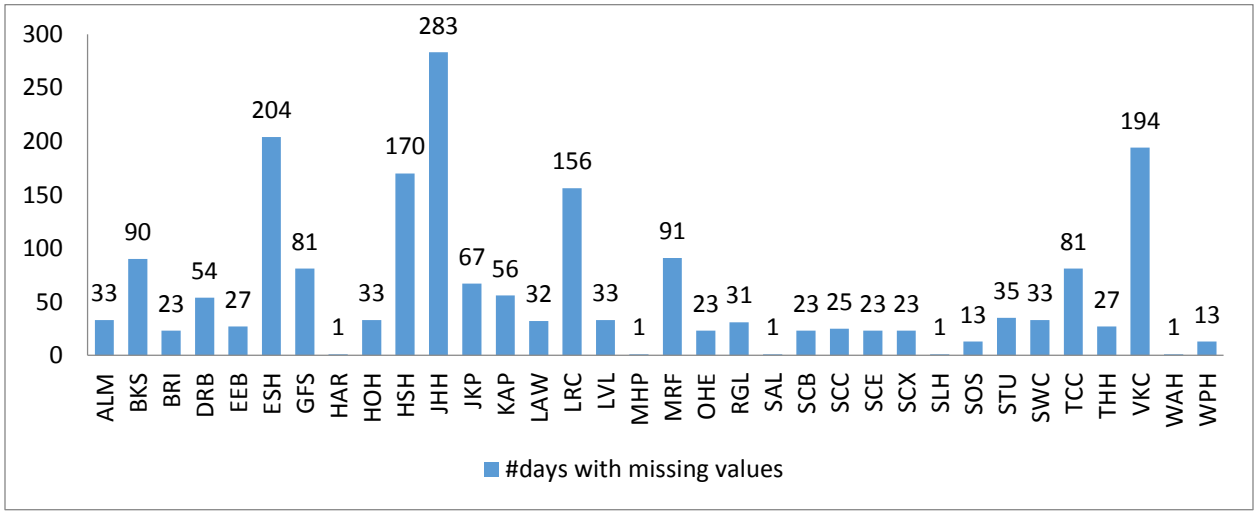


Figure 21: List of buildings having one or more days with missing data points (July 17 2012 – July 17, 2014).

2- Observed kWh:

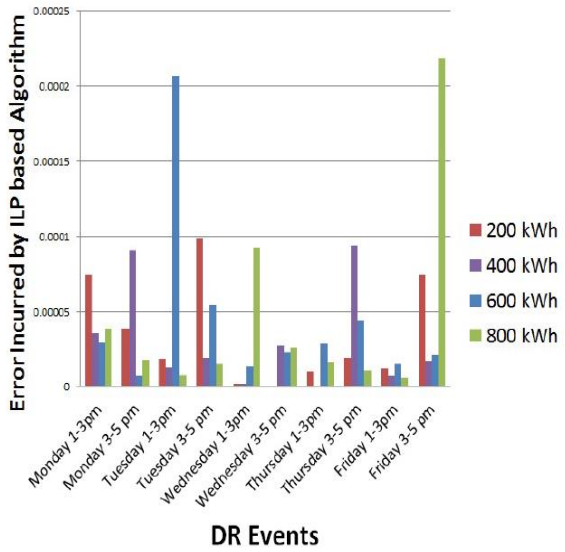
For the observed kWh the likely cause for the fluctuations in the estimates are caused by the variability in some of the buildings' consumption during curtailment. The plots at the end of the report illustrate some examples of buildings with consumption fluctuations.

Method Selection for Electricity Consumption Forecasting:

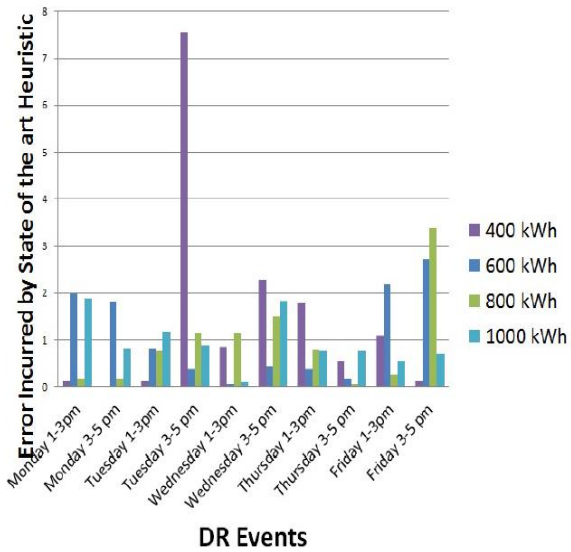
In this demonstration, an efficient ANN (Artificial Neural Network) based method for selecting the best consumption method in smart grids has developed. The method is suited for such environments where no single prediction method can be used due to the various consumption patterns of the customers. The method is more than three times faster than an oracle method which tests each customer against every method. Owing to the fact it does not require frequent retraining it can be applied to online scenarios such as those involving sustaining consumption curtailment in smart grids for several hours. The reason behind its efficiency lies in the training variables that capture the variability in the customer consumption data set. To further reduce the prediction errors induced by traditional methods in use by utilities we have proposed to new methods that capture the consumption variability in an online fashion. The USC VSoE team analyzed their efficiency with respect to the number of times they were selected as the best by the ANN method.

Optimal Building Selection for DR Events:

In this demonstration, an Integer Linear Programming approach was developed for selecting the best subset of customers and corresponding strategies for achieving a given curtailment target value. Optimal customer selection is critical for maintaining system reliability. The developed algorithm guarantees minimum deviation from the target. The Figure below shows quantitatively the error improvement over the state-of-the-art.



(a) ILP based Algorithm



(b) State-of-the-Art Algorithm

Figure 22: Error incurred by the USC VSoE team's ILP based algorithm as compared to that entailed by the state-of-the-art algorithm for various target Curtailment Values across numerous DR events.

9 Summary of Accomplishments

The summary of accomplishments in this demonstration is listed below:

- **Adaptive, Scalable, & Integrated DR Software Architecture**
  - ✓ Conditions & scenarios change over time (e.g. customers change, building use profile changes) and over space (e.g., different buildings on campus, different customers in DWP). Availability of data and features may also change
  - ✓ Solution that can perform continuous learning and is able to scale to 52,000 customers or more using reasonable computation hardware
  - ✓ Can be integrated with other components such as FMS Information & Control Systems, customer behavior models and DWP Software Stack
- **On campus curtailment of 1.2 MW**
  - ✓ 52 residential and non-residential buildings
  - ✓ analysis of 7-years' of data
  - ✓ analysis of 6 DR strategies
- **Validation of campus results on DWP customers**
  - ✓ Forecast method analysis
    - controlled equipment Vs. voluntary DWP customer actions
  - ✓ Demand Response Decision Support System (DDS 1.1) API delivered to the DWP for integration
    - forecast & curtailment methods
- **Automatic & dynamic customer selection policy**
  - ✓ Customer grouping based on curtailed kW
  - ✓ API for linking with FMS control node
  - ✓ Policy Engine software
- **Research Contributions**
  - ✓ Over 25 publications in journals such as IEEE Transactions, and conferences and workshops including AAAI, ACM BuildSys, SmartGridComm, GreenIT, SoCalSGS
  - ✓ More than 10 Technical Reports and Posters
  - ✓ Winner software of the 5th IEEE International Scalable Computing Challenge at CCGrid in Ottawa Canada, 2012
  - ✓ 12 PhD students supported plus many Masters students, undergraduate students, and visiting scholars
- **Collection of large electricity consumption datasets**
  - ✓ Data collected every 15 minutes from 170 buildings for more than 7 years resulting in 170 x 7 years x 365 days x 96 intervals = 41.7 million data points

- ✓ Weather data collected from NOAA station on USC campus at a 24 hour frequency
- ✓ Schedule data (i.e., holidays, weekends, vacation) based on USC calendar

10 Lessons Learned

The major lessons learned in DR include the following:

Data Quality and Integrity

- Inconsistency of input data which is introduced by changes in equipment.
- Arbitrary unavailability of data at random time periods due to diverse factors resulting in missing data.
- Systematic unavailability of data for known time periods for a known subset of smart meters, due to non-transmission of data in that period, known as the "partial data problem".
- Change in DR event schedules resulting in a rescheduling of the event.
- Canceled/aborted DR events due to various reasons.

Scalability

- Run-time scalability and scalability of stream processing are the key requirements for handling high velocity variable-rate data streams.
- Testing

Software Integration

- Adapting DDS to be compatible with FMS despite changes.
- Adapting software according to the changing requirements.

Evaluation

- Prediction Performance using various metrics.
- Optimization for customer selection.

11 Publications/Conference Papers Written

A list of publications by the USC VSoE team follows:

2016

1. Sanmukh R. Kuppannagari, Rajgopal Kannan, Charalampos Chelmis, Arash S. Tehrani, and Viktor K. Prasanna, *Optimal Customer Targeting for Sustainable Demand Response in Smart Grids,* International Conference on Computational Science, 2016.
2. Ranjan Pal and Viktor Prasanna, *The STREAM Mechanism to Improve CPS Security The Case of the Smart Grid,* IEEE Transactions on Computer-Aided Design for Integrated Circuits and Systems, 2016.
3. Fabian Knirsch, Dominik Engel, Cristian Neureiter, Marc Frincu and Viktor Prasanna, *Privacy Assessment of Data Flow Graphs for an Advanced Recommender System in the Smart Grid,* Communications in Computer and Information Science, Springer, Vol 576, 2016.
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6. Sanmukh R. Kuppannagari, Rajgopal Kannan, Charalampos Chelmis and Viktor K. Prasanna, *Automated Dynamic Demand Response Implementation on a Micro-grid,* 3rd ACM International Conference on Systems for Energy-Efficient Built Environments, 2016.
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8. Michail Misyrlis, Charalampos Chelmis, Rajgopal Kannan and Viktor K. Prasanna, *Sparse Causal Temporal Modeling to Inform Power System Defense*, Complex Adaptive Systems, Procedia Computer Science, 2016.
9. Charith Wickramaarachchi, Sanmukh R. Kuppannagari, Rajgopal Kannan and Viktor K. Prasanna*, Data Attack on Strategic Buses in the Smart-Grid: Design and Protection – Decoded,* IEEE Conference on Technologies for Sustainability, 2016.

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3. Saima Aman, Marc Frincu, Charalampos Chelmis, Mohammad Noor and Viktor K. Prasanna, *Prediction Models for Dynamic Demand Response: Requirements, Challenges, and Insights,* IEEE Conference on Smart Grid Communications, 2015.
4. Charalampos Chelmis, Jahanvi Kolte and Viktor K. Prasanna, *Big Data Analytics for Demand Response: Clustering Over Space and Time,* IEEE International Conference on Big Data Workshops, 2015.
5. Ranjan Pal, Charalampos Chelmis, Chandra Tadepalli, Marc Frincu, Saima Aman and Viktor Prasanna, *Online Time Series Clustering for Demand Response: A Theory to Break the 'Curse of Dimensionality',* ACM e-Energy, 2015.
6. Marc Frincu, Charalampos Chelmis, Saima Aman, Muhammad Rizwan Saeed, Vasilis Zois, Viktor Prasanna, Carol Fern and Aras Akbari, *Enabling Automated Dynamic Demand Response: From Theory to Practice,* ACM e-Energy, 2015.
7. Charalampos Chelmis, Muhammad Rizwan Saeed, Marc Frincu and Viktor Prasanna, *Curtailment Estimation Methods for Demand Response: Lessons Learned by Comparing Apples to Oranges,* ACM e-Energy, 2015.
8. Saima Aman, Yogesh Simmhan and Viktor K. Prasanna, *Holistic Measures for Evaluating Prediction Models in Smart Grids,* IEEE Transactions on Knowledge and Data Engineering, Vol. 27, No. 2, pp: 475-488, 2015.
9. Fabian Knirsch, Dominik Engel, Marc Frincu, Viktor Prasanna, *Model-based Assessment for Balancing Privacy Requirements and Operational Capabilities in the Smart Grid,* IEEE Conference on Innovative Smart Grid Technologies, 2015.
10. Fabian Knirsch, Dominik Engel, Christian Neureiter, Marc Frincu, Viktor Prasanna, *Model-driven Privacy Assessment in the Smart Grid,* International Conference on Information Systems Security and Privacy, 2015. (Best Paper Award)
11. Saima Aman, Charalampos Chelmis and Viktor K. Prasanna, *Influence-driven Model for Time Series Prediction from Partial Observations,* AAAI Workshop on Computational Sustainability, 2015.
12. Charalampos Chelmis, Saima Aman, Muhammad Rizwan Saeed, Marc Frincu and Viktor K. Prasanna, *Estimating Reduced Consumption for Dynamic Demand Response,* AAAI Workshop on Computational Sustainability, 2015.
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18. Charalampos Chelmis, Jahanvi Kolte, and Viktor K. Prasanna, *Patterns of Electricity Demand Variation in Smart Grids*, Technical Report, University of Southern California, 2015.
19. Ranjan Pal, Charalampos Chelmis, Marc Frincu, and Viktor K. Prasanna, *Time Series Clustering for Demand Response: An Online Algorithmic Approach*, Technical Report, University of Southern California, 2015.

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5. Alok Kumbhare, Marc Frincu, Cauligi S. Raghavendra, and Viktor K. Prasanna, *Efficient extraction of high centrality vertices in distributed graphs*, High Performance Extreme Computing Conference, 2014.
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7. Yogesh Simmhan, Alok Kumbhare, Charith Wickramaarachchi, Nam Ma, Soonil Nagarkar, Santosh Ravi, Cauligi Raghavendra, and Viktor K. Prasanna, *GoFFish : A Framework for Distributed Analytics Over Timeseries Graphs*, Technical Report, University of Southern California, 2013.

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4. Qunzhi Zhou, Yogesh Simmhan and Viktor Prasanna, *Incorporating Semantic Knowledge into Dynamic Data Processing for Smart Power Grids,* International Semantic Web Conference, 2012.
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6. Qunzhi Zhou, Yogesh Simmhan and Viktor K. Prasanna, *Semantic Complex Event Processing over End-to-End Data Flows,* Computer Science Department, University of Southern California, 2012.
7. Yogesh Simmhan, Litao Deng, Alok Kumbhare, Mark Redekopp and Viktor K. Prasanna, *Scalable, Secure Analysis of Social Sciences Data on the Azure Platform*, Cloud Futures Workshop, 2012.
8. *Qunzhi Zhou, Yogesh Simmhan, and Viktor K. Prasanna, SCEPter: Semantic Complex Event Processing over End-to-End Data Flows*, Technical Report, University of Southern California, 2012.

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1. Saima Aman, Yogesh Simmhan and Viktor K. Prasanna, *Improving Energy Use Forecast for Campus Micro-grids using Indirect Indicators,* International Workshop on Domain Driven Data Mining , 2011.
2. Saima Aman, Wei Yin, Yogesh Simmhan and Viktor Prasanna, *Machine Learning for Demand Forecasting in Smart Grid,* Southern California Smart Grid Research Symposium, 2011.
3. Yogesh Simmhan, Alok Kumbhare, Baohua Cao and Viktor K. Prasanna, *An Analysis of Security and Privacy Issues in Smart Grid Software Architectures on Clouds* International Cloud Computing Conference, 2011.
4. Alok Kumbhare, Yogesh Simmhan and Viktor Prasanna, *Designing a Secure Storage Repository for Sharing Scientific Datasets using Public Clouds,* International Workshop on Data Intensive Computing in the Clouds, 2011.
5. Yogesh Simmhan, Saima Aman, Baohua Cao, Mike Giakkoupis, Alok Kumbhare, Qunzhi Zhou, Donald Paul, Carol Fern, Aditya Sharma and Viktor K. Prasanna, *An Informatics Approach to Demand Response Optimization in Smart Grids,* University of Southern California, 2011.
6. Yogesh Simmhan, Viktor Prasanna, Saima Aman, Sreedhar Natarajan, Wei Yin and Qunzhi Zhou, *Towards Data-driven Demand-Response Optimization in a Campus Microgrid,* Workshop On Embedded Sensing Systems For Energy-Efficiency In Buildings, 2011.
7. Yogesh Simmhan, Qunzhi Zhou and Viktor K. Prasanna, *Chapter: Semantic Information Integration for Smart Grid Applications,* pp. 361-380, Springer Berlin Heidelberg, 2011.
8. Qunzhi Zhou, Sreedhar Natarajan, Yogesh Simmhan and Viktor Prasanna, *Semantic Information Integration and Processing for Demand Response Optimization,* Southern California Smart Grid Research Symposium, 2011.
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10. Yogesh Simmhan, Baohua Cao, Michail Giakkoupis and Viktor K. Prasanna, *Adaptive rate stream processing for smart grid applications on clouds,* International Workshop on Scientific Cloud Computing, pp. 33-38, 2011.

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1. Saima Aman, Yogesh Simmhan and Viktor K. Prasanna, *Smart Communication of Energy Use and Prediction in a Smart Grid Software Architecture,* IEEE Coastal Los Angeles Section, 2010

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Saima Aman, Prediction Models for Dynamic Decision Making In Smart Grid, 2016

Alok Kumbhare, Adaptive and Resilient Stream Processing on Cloud Infrastructure, 2016

Qunzhi Zhou, A Complex Event Processing Framework for Fast Data Management, 2014

12 Software Deliverables

12.1 DDS Source Code

Important Deliverable classes (java) are as follows:

ARIMAConsumptionModel

ARIMAConsumptionModelFactory

ARIMAConsumptionTestClient

ARIMAConsumptionTrainer

ARIMAModel

ARIMAModelFactory

ARIMATrainer

AveragingCurtailmentModel

AveragingCurtailmentModelFactory

AveragingCurtailmentTestClient

AveragingCurtailmentTrainer

BaselineConsumptionModelFactory

BaselineConsumptionTestClient

BaselineConsumptionTrainer

CAISOModel

CASCEModel

ClusteringGroupConsumptionModel

ClusteringGroupConsumptionTrainer

ClusteringGroupCurtailmentModel

ClusteringGroupCurtailmentTrainer

DirectCurtailmentModel

DirectCurtailmentTrainer

NYISOModel

WekaConsumptionTestClient

WekaDataDrivenConsumptionModel

WekaDataDrivenConsumptionModelFactory

WekaDataDrivenConsumptionTrainer

WekaDataDrivenModel

WekaDataDrivenTrainer

WekaTestClient

New k-means based clustering algorithms (matlab)

12.2 PolicyEngine

Appendix N Cyber Security for Smart Grid:Final Progress Report

LADWP Smart Grid

Cyber Security for Smart Grid:

Final Progress Report

June 20, 2016

Document Change History

Date	Version	State	Change Description
6/2/2016	0.1	Draft	Initial draft release
6/20/2016	1.0		Revisions based on review of document.

Preface

This document describes progress by the Los Angeles Department of Water and Power (LADWP) in establishing the cyber security of the smart grid. This work was carried out by LADWP Information Technology Services (ITS), and by the Jet Propulsion Laboratory (JPL).

To provide context, this document includes descriptions of JPL's recent work, which was funded solely by LADWP (outside LADWP's DoE-funded Smart Grid Regional Demonstration Project, or SGRDP) as well as some of the foundation work performed as part of the SGRDP on which the more recent work is based.

Under the auspices of the SGRDP, the basic Detection, Diagnosis, and Remediation (DDR) design was established and the initial implementations of the AMI data collector (developed by USC ISI), the DDR database, the DDR data monitors, and some prototype detectors were completed.

Under the auspices of the LADWP-funded effort, the design was refined to support additional capabilities, many of the existing components were improved, and some new components were implemented (new detectors and diagnosticians, alert emitter, simulated data injector, and DDR local visualization tools). This work builds on the prior SGRDP work to advance LADWP's goals in the area of securing the smart grid.

Acknowledgements

This work was carried out by LADWP Information Technology Services (ITS), and by the Jet Propulsion Laboratory (JPL), California Institute of Technology, under a contract with the Los Angeles Department of Water and Power.

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Introduction

Document Purpose

The purpose of this document is to describe the recent cyber security work for the smart grid that was carried out by LADWP ITS and JPL.

Objectives

This document provides:

A high-level description of the system architecture of two key systems deployed as part of LADWP's smart grid cyber security approach

A description of the algorithms used to detect security-related events within the LADWP smart grid environment

A summary of the preliminary data analyses performed on source data for the systems

The outlines of selected scenarios that demonstrate the application of those algorithms to problems of interest to LADWP

Systems Capabilities Overview

The LADWP approach to cyber security for smart grid includes a number of deployed and planned systems. This document focuses on two of the deployed systems: the Cyber Security (CS) Detection, Diagnosis, and Remediation (DDR) system, and the Security Information and Event Management (SIEM) system.

The CS DDR system obtains security-relevant data from a number of sources within the LADWP smart grid, detects and diagnoses cyber security-related events by analyzing these data, and sends these events to the SIEM system for logging, display, and operator action.

The LADWP Smart Grid SIEM system receives security-related data from CS DDR and other data sources, stores that data in its database, and provides capabilities to monitor, visualize, and provide reports on those data.

DDR System Capabilities Overview

The DDR has the capabilities summarized below. DDR can:

Advanced Metering Infrastructure (AMI)

Connect to the operational AMI Data Collection Engine (DCE) running at LADWP to obtain meter usage data, meter events, and meter exceptions from AMI meters.

Obtain Connected Gateway-Network Management System (CG-NMS) data from AMI (via the SIEM system)

Store that operational AMI meter and network data in DDR database.

Generate selected simulated meter data and store those in the DDR database.

Perform detection and diagnosis of real and/or simulated meter-related events from the operational and/or simulated meter data, possibly in combination with other data sources

Provide selected simple visualizations to aid in demonstrating detectors.

Demand Response (DR)

Obtain records of DR application events and related data from DR log files via an agent installed on the DR machine.

Store those records in an operational DDR database.

Electric Vehicles (EV)

Obtain records of EV events from EV log files via an agent installed on the EV machine.

Store those records in an operational DDR database.

LADWP Intrusion Protection System (IPS)

Obtain records of network intrusions and anomalies detected by LADWP's commercial IPS.

Store those records in an operational DDR database.

SIEM System Capabilities Summary

The smart grid SIEM implementation at LADWP consists of the following:

Visualization and monitoring of DDR events

Mass meter disconnect

Denial of Service (DoS) attacks against smart meter communication infrastructure

Potential energy theft

Infrastructure system change detection and diagnosis

DDR firewall alerts and actions

Visualization and monitoring of smart grid infrastructure health and security events

Smart meter communication infrastructure alerts and events

Smart meter alerts and events

Smart meter key management system alert and health

Smart grid zone firewall alerts

DDR Architecture

The top-level architecture of CS DDR is shown i**n** Figure 0-1. The components are described in the sections below.

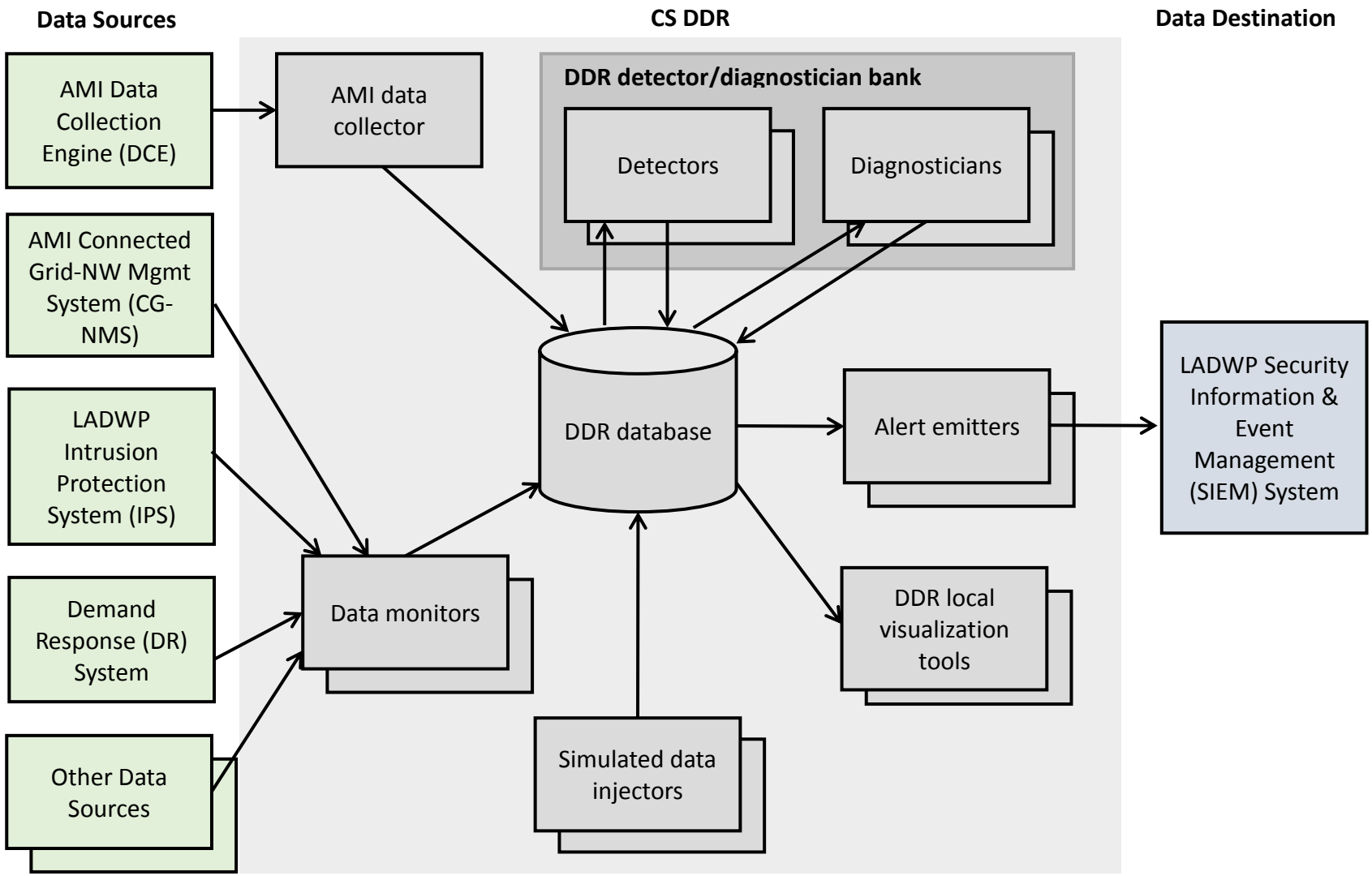


Figure 0-1: CS DDR Architecture

AMI Data Collection Engine (DCE) Interface Software

The **AMI DCE interface software** subscribes to the DCE for meter-related data of interest, receives the data from DCE, and writes the data to the DDR database.

Data Monitors

The data monitors interface to various data sources and obtain security-relevant data from those sources. This is normally accomplished by installing monitoring agents on the data sources, which transmit data to the data monitors within DDR. The DDR data monitors store the raw monitor data in the DDR database and, in some cases, perform additional processing of the data to facilitate their use in detection and diagnosis. Such processed data is also stored in the DDR database.

Simulated Data Injectors

The simulated data injector generates simulated meter data. The injector is used, for example, to create data containing simulated anomalies, statistically significant larger data sets, a fault-injected test corpora, and so on. The use of data injectors was necessary for evaluating defensive capabilities in scenarios in which deploying real attacks (or failures) within the operational system was simply not viable *(e.g.*, testing detection capabilities for CGR failures that may be the consequence of DoS attacks).

The output format for the simulated data is the same as the format of the original data, except that there is an indicator flag in each record identifying whether the data comes from an operational source or from the simulated data injector.

DDR Database

The DDR database is the central repository for data received by DDR, as well as other data generated by DDR internally (*e.g.*, detected events, meta data regarding system health, etc.). Raw data from external data sources, intermediate data sets, and DDR-generated alerts are all stored in the database.

Detector and Diagnostician Bank

The detector and diagnostician bank is designed to contain a diverse set of detectors and diagnosticians. The detectors and diagnosticians analyze source data – and/or the events output by other detectors and diagnosticians – to identify alerts of interest in those data. This may involve the correlation (in space, time, or other ways) of data from multiple sources.

The infrastructure is designed to be flexible, in that it allows the incorporation of new detection and diagnosis algorithms that may be better suited to new and evolving threat scenarios. The detector bank writes detection/diagnosis alerts back to the DDR database.

Selected detection and diagnosis algorithms are described in Section 0. Some preliminary data analyses performed on DDR data sources used for detection and diagnosis are described in Section 0. Demonstration scenarios for selected detections and diagnoses are described in Section 0.

DDR Local Visualization Tools

The DDR local **visualization tools** obtain selected events of interest from the DDR database and displays them locally to the DDR system. While these basic visualizations have been implemented for internal use within DDR itself, the SIEM system is the primary tool that operators use to visualize and act on security-related events. The SIEM system is described further in Section 0.

DDR Alert Emitters

The DDR **alert emitters retrieve** selected events of interest from the DDR database and transmit them to the LADWP SIEM system for display and operator review and action.

The DDR Alert Emitters continually check the DDR database for new alerts and, when they appear, send them as messages to the SIEM system. If the DDR Alert Emitters are stopped or fail, they are automatically restarted. Once restarted, the emitters will resume processing where they left off the last time they ran. This ensures that all alerts are sent.

DDR Detection and Diagnosis Algorithms

Energy Theft Detection Algorithms

Objective

Energy theft in the smart grid may be perpetrated by a utility customer who tampers with his smart meter to modify stored and/or reported power usage. The objective of the energy theft detection algorithm is to detect potential energy theft attempts by correlating unusually low usage readings and security events from AMI meters.

High-Level Overview of Algorithm

Inputs: The algorithm relies on the following two key data inputs:

Meter Watt-hour (KWh) readings

Meter Events belonging to any of the following four categories: *Status Event*, *Power Outage or Restoration*, *Configuration*, or *Billing Event*.

Outputs:

The algorithm can raise one of four possible alerts, each corresponding to a possible explanation of the detected anomaly in the meter readings, namely:

Anomalous usage due to potential energy theft attempt

Anomalous usage due to meter failures

Anomalous usage due to loss of power

Anomalous usage due to meter being disconnected

Algorithm:

The algorithm works in two stages.

In the first stage, the algorithm periodically monitors meter usage data (KWh data) for each meter to detect instances of consecutive low usage, and raises an alert if such an instance is detected.

In the second stage, the algorithm reads the consecutive low usage alerts, and tries to find a potential cause for those alerts. It does so as follows:

It first searches for AMI meter events within ±15 minutes of the occurrence of the consecutive usage alert.

Any events found are first sorted by their time of occurrence, and then analyzed using a state machine to infer a potential cause. The state machine is built using knowledge of the AMI deployment, and can currently result in one of four potential causes

Potential Energy Theft Attempt

Potential Meter Failure

Potential Loss of Power

Potential Loss of Power Due to Meter Disconnect

A corresponding alert is raised, if a cause is found.

AMI Connected Grid Router Unavailability (DoS) Detection Algorithms

Objective

A malicious attacker can perform a denial of service (DoS) attack against an AMI Connected Grid Router (CGR) in the smart grid, thereby disrupting the communication between the smart meters and the utility. A DoS against a CGR might not necessarily shut down the CGR, but rather affect the latency of the meter reads, and/or cause failed reads. Thus, it is not always possible to rely solely on CGR events to infer the state of a CGR. The objective of this initial algorithm is to infer the state of a CGR by correlating failed meter reads from AMI meters connected to the CGR.

High-Level Overview of Algorithm

Inputs: The algorithm relies on the following two key data inputs:

Meter KWh readings (aggregated daily)

A model of the AMI network topology, containing a mapping of AMI meters to CGRs.

Outputs:

The algorithm outputs a single type of alert if a CGR is unavailable, but it varies its severity based on the computed percentage of failed reads behind the CGR. The severity is set as follows:

Percent of meters down (failed reads)	**Severity**
≥ 95%	Emergency
≥ 80%	Alert
≥ 70%	Critical
≥ 50%	Warning

Algorithm:

The algorithm works in two stages.

In the first stage, the algorithm periodically monitors daily meter usage data (KWh data) for each meter to detect instances of consecutive reporting failures. That is, it raises an alert if a meter has not reported for 'k' consecutive days.

In the second stage, the algorithm reads the consecutive failure alerts, and performs a spatio-temporal correlation of those alerts as follows:

Index the consecutive failure alerts by date.

For each date

For each alert on that date

Extract meter ID from alert

Find CGR corresponding to the meter using the meter to CGR topology map (which is input to the algorithm)

Add meter ID to list of failed meters behind CGR.

Go through the list of failed meters for each CGR, compute percentage of failed reads, and raise alerts

Mass Remote Meter Disconnect Detection Algorithms

Objective

A mass remote disconnect attack happens when a large number of meters are disconnected within a short span of time. From a power grid operations perspective, a remote disconnect has the effect of removing load from the grid. Thus, a sufficient number of remote disconnects within a short span of time has the potential to cause a sudden load drop and lead to grid instability.

A remote disconnect command is used to disconnect power to a customer. Typically, meter disconnection has been performed manually by a technician, but a remote disconnect allows this process to be automated. Whenever a meter receives a remote disconnect command from the AMI Data Collection Engine (DCE), it acts on the command, and sends back a remote disconnect success (or failure) exception.

The objective of this detector is to detect a mass remote disconnect of AMI meters, by monitoring the rate of "remote disconnect success" exceptions from the meters to the DCE, and alerting when the rate exceeds a pre-specified threshold.

Detecting a mass remote disconnect of meters can be performed in at least the following ways:

Monitor the *rate of "remote disconnect commands"* being sent from the DCE to meters, and detect sudden inflections in the rate.

Monitor the *rate of "remote disconnect success exceptions"* from meters to the DCE and detect sudden inflections in the rate.

Monitor the cumulative load situation on the grid using power consumption data to detect a sudden load drop on the grid.

Approach (3) can only detect the consequence of the mass disconnects and might not be able to localize the cause to a remote disconnect attack easily. Further, it requires access to accurate and real-time power data from the grid. Approaches (1) and (2) are the most promising for detecting an attack in progress, and alerting an operator before the attack affects the grid. However, since we don't yet have

access to data about "remote disconnect commands" being sent to the meters, for the purposes of demonstration, we restrict our focus to approach (2) for detecting mass remote-disconnect attacks.

High-Level Overview of Algorithm

Inputs: The algorithm relies on the following key data input:

Remote disconnect success exceptions from meters

Outputs:

The algorithm outputs a *Mass Remote Disconnect Attack* alert, if the rate of input events exceeds a threshold.

Algorithm:

The algorithm runs continuously (each minute) and performs the following steps during each iteration:

Update a rolling buffer of size *k* (where *k* is the window length in minutes)

Count the number of "remote disconnect success" exceptions received during the last minute.

Add to the rolling buffer.

Compute the average of the exceptions received in the buffer over the window size *k.*

Generate an alert if the average exceeds a threshold.

Other Algorithms Investigated

We conducted preliminary investigations into two other, separate approaches to performing energy theft detection in the smart grid, based purely on the usage data reported by meters. The initial results were encouraging but would require further thorough experimentation and analysis to convert them into detection algorithms.

The first approach explored a clustering-based strategy to detect potential energy theft by malicious customers by monitoring anomalous movements of customers' usage patterns among different computed patterns of energy usage, as represented by clusters of usage patterns. For example, sudden movement of a customer from a high usage cluster to a low usage cluster may be indicative of energy theft.

Towards that goal, we systematically investigated several clustering algorithms, and cluster validation techniques on different data sets, and characterized their applicability with respect to the energy theft scenario. Specifically, we investigated six clustering algorithms: *k-means*, a*gglomerative*, *DBSCAN*, *affinity propagation*, *Gaussian mixtures*, and *mean-shift*. We found the *k-means*, *agglomerative*, and *affinity propagation* algorithms to be the most promising for building clusters from the energy usage data set.

We also investigated cluster validation techniques, which provide statistical measures of the "goodness" of the results of the application of a clustering algorithm to a data set. Specifically, we investigated two external cluster validation techniques, *precision* and *recall*, and six internal cluster validation techniques: *Dunn*, *CH-Index*, *DB-index*, *Silhouette*, and *SD-index*, and found that the *CH-index* offered the most promise for validating the clusters.

The anomaly detector that we developed first groups the training data set into a specific number of clusters, and then given a test data set (from the same population of meters as the training set), assigns the meters in the test set to a cluster (from the learned model) to which they are closest, according to the similarity measure dictated by the clustering algorithm. A meter that shifts from its initial cluster assignment to a different cluster is then flagged as potentially anomalous. We measured the effectiveness of this detector in flagging anomalies by using synthetically created test sets with labeled anomalies so that precision and recall could be calculated. Initial testing revealed that the detector could identify anomalous behavior when the customer reduced their energy consumption by ~45% or more, although these results are very preliminary.

A key advantage of this approach is that it potentially enables detecting customers who might engage in energy theft by maliciously inducing a percentage-based reduction in their energy usage. For example, a malicious customer might arrange to report a percentage of his actual energy consumption, instead of reporting zeroes or some fixed values, to evade simple detection. Other simpler approaches, such as the one discussed in Section 0, will fail to detect these advanced energy theft methods but the clustering-based approach would flag such cases.

The second algorithm investigated was a density-estimation based approach to anomaly detection. In this approach, each meter is modeled individually based on historical energy usage data from the meter, and anomaly detection is then performed by computing deviations from the model.

The data set for each customer consists of a matrix of *m* rows and 25 columns, where *m* is the number of days. Energy usage on each day is represented as a 25-element vector, where the first 24 elements are energy readings (Wh) for each hour of the day, and the 25th element is the temperature recorded on that day. We split this data set into the training set, the test set, and a cross-validation set.

At a high-level the algorithm works as follows:

We use the training set to estimate the Gaussian distribution for each of the features. Specifically, we compute the mean (x_i) and variance (σ_i^2) for each of the features, where i is one of the 25 features. This forms the model.

Given a new data sample x, that is, a new 25-element vector, we compute the probability of occurrence of that sample $p(x)$ as $p(x_1; \mu_1, \sigma_1^2) \times \ldots p(x_{25}; x_{25}, \sigma_{25}^2)$

If $p(x) < \epsilon$ (say 0.01), we flag the sample x as anomalous. The value of ϵ is determined using the cross-validation set.

This approach is promising, but one of the main difficulties we encountered for validating this algorithm was the lack of real-world anomalous samples. Our initial testing was performed using simulated anomalous samples, although the models were trained using real data from the meters.

Preliminary Analyses of DDR Data Sources

Preliminary analyses of some of the DDR data sources are described in this section. These analyses were conducted to characterize the data received, and to investigate the utility of these data for detection and diagnosis of security-related events.

AMI Network Latency Experiments for Remote Disconnects

Objective

We conducted a series of experiments on the LADWP AMI network to gather necessary data required to build analytical models, in support of the following objectives:

Compute the theoretical rate (maximum/minimum/average) at which commands (say a *remote disconnect*) can be sent from the DCE to meters assuming a healthy AMI network.

Compute the average time for a message to travel from the DCE to a meter, and vice versa.

The results from these experiments allow us to simulate – with a greater degree of fidelity to the operational system – the latency characteristics of network communications to and from the meters. This in turn enables us to understand the impact to the operational system should, for example, an adversary issue a remote disconnect command to 40% of the meters. In such a case, can an instantaneous shut down of all those meters occur? Or will the inherent latencies within communication network stagger the effect of the meter disconnects?

Experiment Design and Methodology

Meter pings were performed using C12.22 ping command from the AMI DCE console. This ping does not provide the round-trip time (RTT) or the number of hops required to reach the destination (unlike a traditional network ping). It is merely a way to check if an endpoint is alive. Nevertheless, we can approximately measure the DCE-meter RTTs using the *Job Start Time* and *Job End Time* logged by the DCE. CGR pings were performed via the CG-NMS. Both the AMI and CGR pings were performed manually.

Two factors were considered while performing the experiments:

Time of day (since results will vary when AMI network is quiet vs. when its busy) –

The network is *busy* during the following times when the meter reads are in progress: 8:00 am–10:00 am, 4:00 pm–6:00 pm, and 12:00 am–2:00 am. The network is assumed to be *quiet* at all other times.

CGR density (number of meters/CGR) – The number of meters per CGR impacts the latency. In the current LADWP deployment, there may be between 600–2000 meters per CGR.

Experiments

A total of six experiments were performed:

Ping each of the 56 CGRs in the system when the network is relatively quiet.

Ping each of the 56 CGRs in the system when the network is busy.

Ping a randomly chosen set of two meters behind each CGR in the system when the network is relatively quiet.

Ping a randomly chosen set of two meters behind each CGR in the system when the network is busy.

Send a ping to 10 meters behind each of three CGRs when network is quiet. The CGRs were chosen based on their density: one each of low, medium and high density CGR was chosen.

Send a ping to 10 meters behind each of three CGRs when network is busy. The CGRs were chosen based on their density, and one of each low, medium and high density CGR was chosen.

Discussion of Results

The following observations were made from the results of the above experiments:

The busier the network, the lengthier the RTT. This is not surprising.

We also saw variations in RTT due to the density of the network, although this was not clear in all the cases. We later learned that there were several other factors which can significantly affect the network latency, such as: temperature, and the locations of meters (*e.g.*, in basement or outside).

Nevertheless, the results were used to construct an approximate model of the AMI network latencies, which was later used for injecting simulated data for the demo scenarios.

AMI Meter Usage Data Analysis

DDR receives several types of AMI meter data from the AMI DCE, including AMI load profile channel (LPC) data (Wh, Vh, etc.), AMI register data, and others. We focused on the AMI LPC Wh usage data and conducted several activities to characterize it, partly to validate the data flow and partly to establish a baseline of nominal activity.

The following sub-sections identify some of the issues encountered during the analysis of the data set, and then provide some figures summarizing key characteristics of the data.

Data Description

The DDR data set for AMI data was established in July 2014 and continues at present (May 2016). There are expected to be approximately 50,000 meters in the data set, each recording usage data at 15-minute intervals and reporting this data three times a day. That is, every year each meter is expected to generate roughly 35,000 readings (4 per hour, 24 hours per day, and 365 days per year) and the current set of meters is expected to generate approximately 1,750,000,000 total readings. This is a substantial data set on which to run analyses.

Results reported in this section were generated using a dataset collected from July 2014 to July 2015.

Spurious Values in Meter Wh Data

While analyzing AMI meter Wh data, we encountered several instances where we discovered seemingly anomalous values. An understanding of these cases is important while processing the meter usage data for billing or any other higher-level analysis. We discuss the two key causes of the spurious values below.

Case 1: Spurious values when meter is in test mode

Consider the data from an operational customer meter as shown below in Table 1-1. The first two columns indicate the time interval over which the Wh value in column 3 is recorded, and column 4 contains the status messages recorded by the meter during that interval. As seen below, the meter suddenly starts reporting very high values (as compared to its normal of ~400 Wh) from 12:30 onwards. Upon further discussion with the AMI team, we learned that these values were generated when the meter was placed in “test mode” by a technician, as is indicated by the status messages. These values must be ignored by higher-level analytical functions such as billing or energy theft detection. The meter Wh values must thus always be interpreted in tandem with the status messages.

Table 1-1: Spurious Meter Data When in Test Mode

Time Interval		**Wh Value**	**Status Messages**
12:15	12:30	474	None
12:30	12:45	19829	"S0" : "TestMode", "S1" : "DaylightSavingsTime”, "S2" : "PowerFailure", "S3" : "ClockResetForward”
13:00	13:15	30254	"S0" : "PowerFailure", "S1" : "ClockResetBackwards”
13:15	13:30	43665	"S0" : "TestMode", "S1" : "DaylightSavingsTime", "S2" : "PowerFailure", "S3" : "ClockResetForward”
< This goes on for 2 more intervals before normal readings resume >			

Case 2: Spurious values due to a potentially faulty meter

Consider the data from a real meter as shown below in Table 1-2. The first two columns indicate the time interval over which the Wh Value in column 3 is recorded, and column 4 contains the status messages recorded by the meter during that interval. We see that the meter suddenly reports an anomalously high-value just for one interval. On further discussion with the AMI team, we understood that these values are probably indicative of a faulty meter if they occur frequently. A higher-level analysis function such as billing should definitely ignore such singleton values, and flag the meter as faulty if such values repeat over time, and exceed a preset threshold (for example, three times within a 24-hour period).

Table 1-2 Spurious Wh values due to a potentially faulty meter

Time Interval		Wh Value	Status Messages
06:30	06:45	167	"S0" : "DaylightSavingsTime”
06:45	07:00	65531	"S0" : "DaylightSavingsTime”
07:00	07:15	223	"S0" : "DaylightSavingsTime”

Data Excluded from Further Analysis

In addition to screening for spurious meter usage values, as described above, analysis of the data led to the identification of other issues with the raw data, which we describe below.

Early Timestamps

Although the DDR data collection began in July 2014, we found usage readings with dates earlier than this. This data turned out to be the result of a test event (demonstrating the ability of the AMI system to back-fill a data gap should the nominal communications path suffer a temporary blockage).

Zero Usage Meters

A few dozen meters, less than 0.01 % of the set, reported zero usage all (or almost all) of the time. Most of these turned out to be test meters.

Mean Power Consumption

Figure 1-2 shows the frequency distribution of mean Wh readings. It reveals a fairly smooth distribution peaking around 80 Wh and tailing off asymptotically. That is to say, most meters report ~80 Wh used every 15 minutes when averaged over time, with the number of customers using more power dropping off at the higher values.

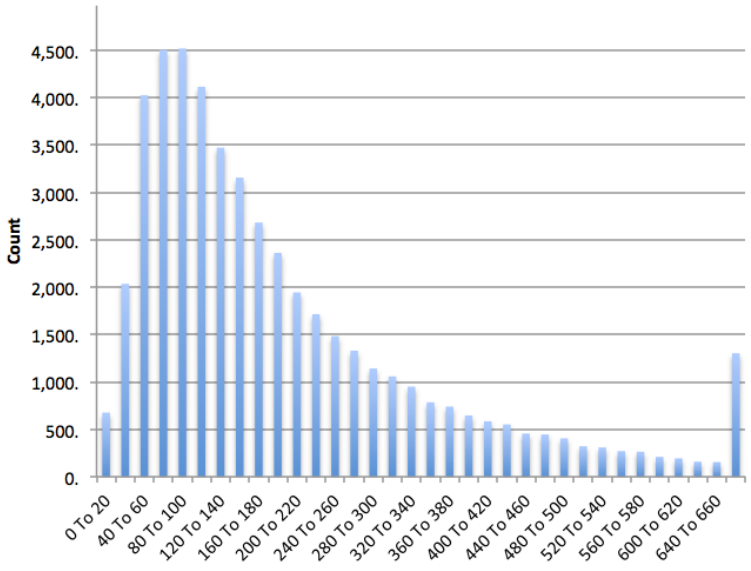


Figure 1-2: Mean Power Consumption Distribution Frequency

Total Power Consumption by Day

Total power consumption per day was summed up across all of the meters and charted by day, then overlaid with a chart of mean daily temperature per day, as shown in Figure 1-3. A heat wave occurred the weekend of September 13, 2014, which correlated with high power usage. The temperature data is for the Los Angeles airport (as recorded at http://www.wunderground.com/history/).

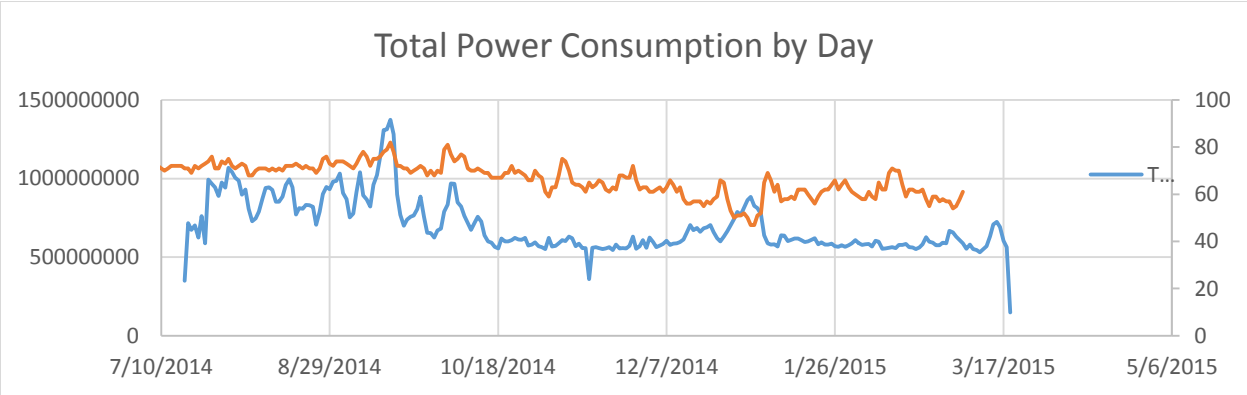


Figure 1-3: Total Power Consumption by Day vs. Temperature

Number of Meters Reporting per Day

The number of meters for which DDR received readings for a given day was seen to vary by several thousand over time, as shown in Figure 1-4.

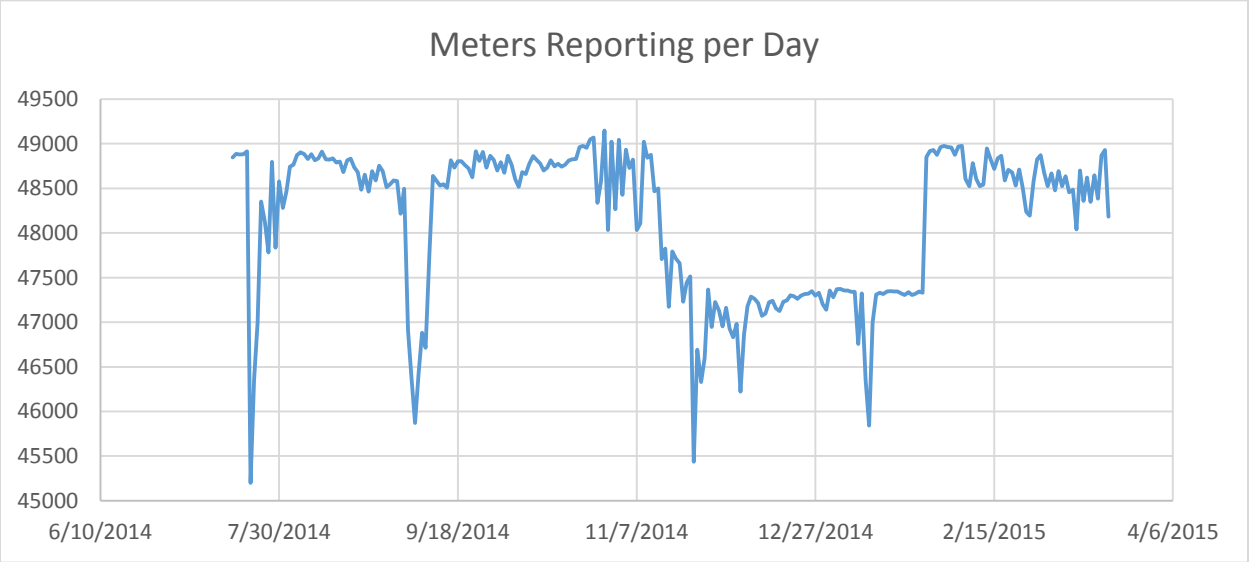


Figure 1-4: Number of Meters Reporting per Day

Number of Meters Reporting Usage by Time of Day

There appear to be a handful of meters with gaps in their reporting intervals each day between 8am and 4pm, as shown in Figure 1-5.

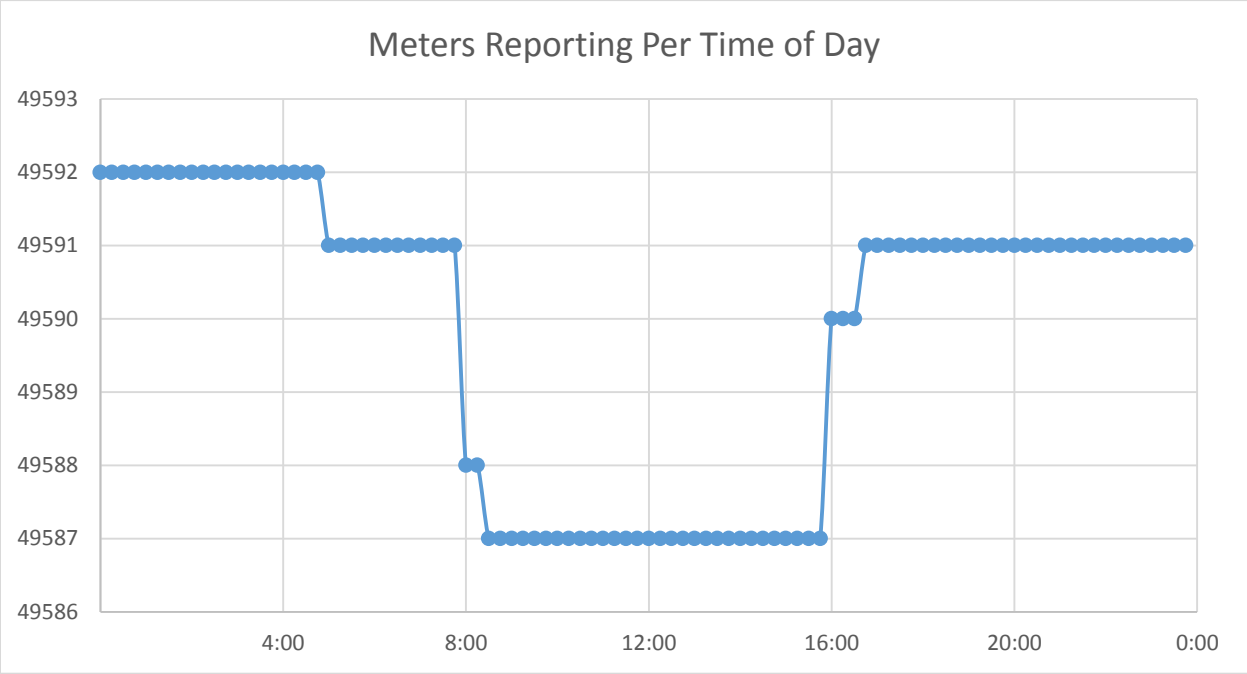


Figure 1-5: Number of Meters Reporting by Time of Day

Power Consumption by Time of Day

Charting the aggregate Wh readings by time interval exposes daily consumption patterns, as shown in Figure 1-6.

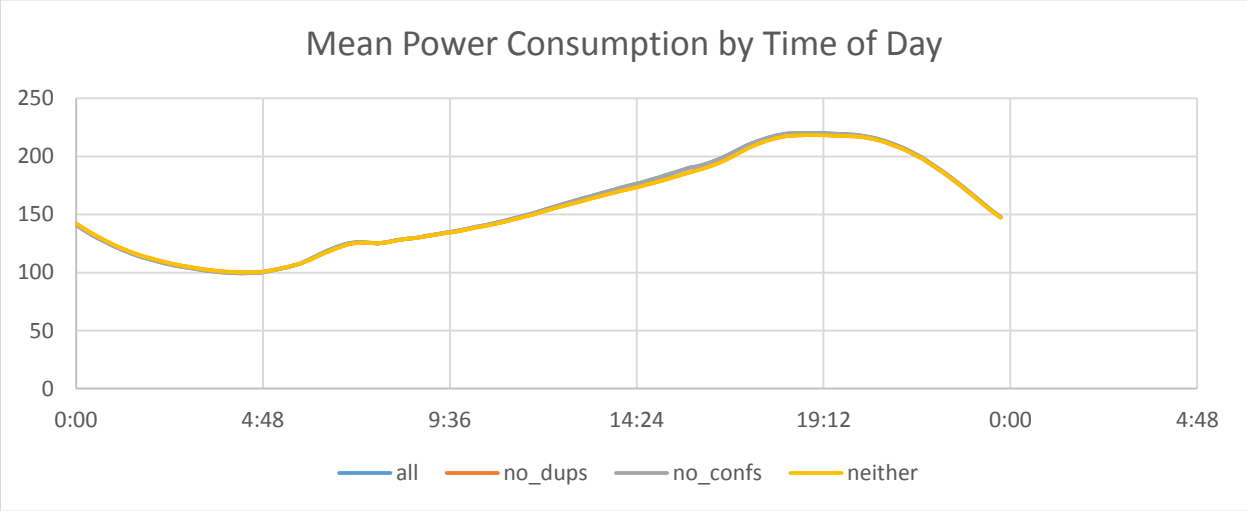


Figure 1-6: Aggregate Mean Power Consumption by Time of Day

AMI Events and Exceptions Data Analysis

AMI meters generate events and exceptions to communicate a variety of information pertaining to their status and health. The data provided in this section is derived from AMI meter data collected over an approximate 18-month period from June 2014 to December, 2015.

AMI Exceptions Statistics

AMI meters initiate the transmission of exceptions under any specific set of circumstances. During the period described above, DDR collected a total of 717,542 exceptions of 27 distinct event types from a total of 46,398 meters. Table 1-3 shows some selected, low-frequency exceptions of potential value for detecting security-related problems, when correlated with other data sources.

Table 1-3: Sample AMI Meter Exceptions

Exception Name	Number of Exceptions	Number of Meters Affected
Test Mode Stopped	7	3
Test Mode Started	9	3
Tamper Attempt Detected	14	5
Fatal Error	36	28
Remote Connect Failed	56	48
Remote Disconnect Failed	85	49
Inversion Tamper	136	109
Remote Disconnect Success	773	265
Removal Tamper	6,763	4,937

AMI Events Statistics

AMI meters record events under a specific set of circumstances, but unlike exceptions, events are only communicated to the DCE during a meter data read. During the period described above, DDR collected a total of 29,610,856 events of 64 distinct event types from a total of 51,204 meters. Table 1-4 below shows some selected events of potential value for inferring meter status, and detecting security-related problems, when correlated with other data sources.

Table 1-4: Sample AMI Events

Exception Name	Number of Events	Number of Meters Affected
Load Voltage Present	6	4
Meter Configuration Changed By Unexpected Source	233	156
Remote disconnect success	450	10
Remote connect success	456	15
Register Firmware Upload Failed	8,256	2,135
Meter Configuration Changed	8,365	8,130
Volt-Hour Restored From Below Threshold to Normal	8,859	1,547
Volt-Hour Below Threshold	9,481	1,487
Register Firmware Upload Initiated	51,199	46,321
Billing Data Cleared	51,569	36,209
Replay Attack	98,239	15,081
Primary Power Down	195,277	43,828
Primary Power Up	200,103	44,512
Meter Reprogrammed	204,784	49,569

AMI Events Relevant to DDR

In this section, we describe semantics of some relevant AMI events which was eventually used to tune our detectors and diagnosticians to ignore irrelevant events, weed out false positives, and produce results relevant to LADWP.

Removal Tamper

A "Removal Tamper" is sent when the meter detects a tilt of 15 degrees or more. An adversary who pulls the meter straight out of the socket can subvert this. Removal tampers can be generated legitimately such as when a technician is disconnecting a customer meter [source: AMI vendor representative, at meeting with AMI team].

Removal tampers, when seen along with other anomalies such as zero usage readings, missed readings, or other meter failures can be indicative of malicious activity, and are thus very relevant for DDR.

Replay Attack

Here is a description of how a "Replay Attack" event is generated [source: email from AMI team]:

Every command generated by the OpenWay Collection Engine has a Time To Live embedded in the command. If the TTL is exceeded and then heard by the meter, the meter generates a Replay Attack event. TTL is +/- 10 minutes of current time (point of reference is the Certicom HSM).

The AMI vendor provides these security measures against a replay attack (source: email from AMI vendor representative to AMI team):

Per our discussion today, the OpenWay Centron will log a Replay Attack event at the meter when the commands time to live has expired. Below is an overview of the OpenWay Enhanced security process:

OpenWay Collection Engine generates a command for the OpenWay Centron

OpenWay Collection Engine sends command to the enhanced security provider (Certicom)

Enhance security provider performs the following actions:

Encrypts the command

Timestamps the command

Digitally signs the command

Enhanced security provider returns the command to the OpenWay Collection Engine

OpenWay Collection Engine sends the command to the field area router (CGR)

The time to live time duration is part of the meter firmware (not adjustable) and is currently configured to 600 seconds.

Given the above description, the "Replay Attack" event may not always indicate an actual attack against a specific meter. But, a large number of these events from several different AMI meters within a region within some period of time, may point to potential issues with the AMI communication network in that region. DDR could potentially correlate such activity along with other events from CGRs and meters to infer Denial of Attacks (DoS) against the meter network.

Reverse Rotation Detected

[source: meeting with LADWP AMI Team]

A "Reverse Rotation Detected" event is generated when a meter is inverted in its socket. An AMI team member mentioned that the deployed smart meters (residential and industrial) are built or programmed in such a way that theft due to reverse rotation is impossible. Some meters (e.g., the 2S form factor meter) are programmed to always record the correct power flow even if inverted, while for others (e.g., form factor 4S meter) the socket design is such that it makes inversion impossible.

Technically, even if a customer is performing this inversion, he will be unsuccessful in his attempts to steal energy, but these events indicate violation of terms of service by the customer must be flagged by DDR. Only solar meters can legitimately generate reverse rotation detection [source: meeting with AMI team].

Inversion Tamper

An "Inversion Tamper" event is generated when the meter detects a tilt. Similar to the above case, this needs to be reported by DDR [source: meeting with LADWP AMI Team]. Further, we observed that EV meters seem to generate the most inversion tampers, but we were unable to investigate the cause of this behavior.

ECDSA Verification Failure

[source: meeting with AMI team].

The "ECDSA Verification Failure" event is generated when the meter fails to verify a message signed with the Elliptic curve and DSA encryption algorithm. This event is of concern because it affects the meter's ability to process messages and act on them, and can be indicative of an underlying problem in the meter. But, this event can also be generated when the meter receives a message (say a read request) while its keys are being initialized before being operationalized.

DDR should generate an alert if this event is received after the meter has been operationalized and has been successfully reporting reads. (Note: Sometimes a meter might be refurbished and reinstalled at a different location, which might cause its keys to be reinitialized).

Unknown Key

An "Unknown Key" event is generated when there is a problem with one of six keys in the meter. Current LADWP meters have keys in slots 1, 3 and 6 [source: meeting with AMI team]. The argument accompanying the event possibly indicates the ID of the unknown key (this is the best guess by an AMI vendor representative).

An "Unknown Key" event could be indicative of internal hardware problems with the meter, or of a potential tamper. DDR should flag a stream of such events as a meter failure. Further, DDR should correlate this event with other security events, and/or configuration change events to infer potential malicious activity.

Fatal Error

A "Fatal Error" event is Indicative of problems in the underlying meter OS and/or hardware [source: meeting with AMI team].

A stream of such events must be flagged by DDR. Further, a fatal error event could be indicative of internal hardware problems with the meter, or a potential tamper. DDR should correlate this event with other security events, and/or configuration change events to infer potential malicious activity.

Replay Attack on Time-Sync Message

A time-sync message is sent by MDM to a meter to synchronize the meter clock whenever the MDM detects that a meter is out of time sync. MDM will only do so if the delta is between 20 and 120 seconds. For larger deltas, a technician must go on the field to inspect the meter. [source: meeting with AMI team].

The "Replay Attack on Time-Sync Message" is generated when a meter receives a "Time-Sync Message" within plus or minus 10 minutes of current time (the point of reference is the Certicom HSM). This is similar to the "Replay Attack" event, except that it is specific to the Time-Sync message.

This event may not always indicate an actual attack against a specific meter. DDR could potentially correlate this event activity along with other security events, or usage data anomalies from the meter to infer potential malicious activity. Further, a large number of these events from several different AMI meters within a region within some period of time, may point to potential issues with the AMI communication network in that region. DDR could potentially correlate such activity along with other events from CGRs and meters to infer Denial of Attacks (DoS) against the meter network.

Meter Configuration Changed

The "Meter Configuration Changed" event is generated when the configuration of the meter is changed. These are infrequent events. This event contains a "name" parameter whose value indicates the type of configuration loaded into the meter, for example "config_*50*_kwh_*demand*_single". There are several types of configuration in use at LADWP.

The "source" parameter value "Openway" indicates that the change was made by DCE, while "fieldtro" indicates that the change was made locally by technician. [source: meeting with AMI team].

DDR could monitor such events to detect unauthorized or unexpected meter changes by correlating them with other auxiliary information such as scheduled configuration changes, and technician work-orders.

Meter Configuration Changed By Unexpected Source

A “Meter Configuration Changed By Unexpected Source” event is generated when a meter is reprogrammed, either via a command received from OpenWay Collection Engine or by a meter technician connecting to the meter via an optical port [source: email from AMI team]. The change source in the above event contains one or two value strings: “Non-exception host” or “Optical”. Similar to the previous case, DDR could monitor such events to detect unauthorized or unexpected meter changes by correlating them with other auxiliary information such as scheduled configuration changes, and technician work-orders.

Meter Reprogrammed

The “Meter Reprogrammed” event is generated if a meter is configured with the same configuration profile it has currently. This happens sometimes when, during a batch update, the reconfiguration of one or more meters fails. In the next configuration update, if a previously successfully configured meter was included, it will generate the above event. [source: meeting with AMI team].

This event does not necessarily indicate any security threat, but a stream of such events from a single meter or across several meters should be flagged by DDR, as it might indicate a problem with the meter update process.

Pending Table Header Changed

The “Pending Table” is where the meter stores firmware downloaded over the network. A “Pending Table Header Changed” event is logged during activation, which means one of the fields in the header has changed [source: email from AMI team].

DDR could monitor such events to detect malicious meter modifications by correlating them with other auxiliary information such as scheduled firmware downloads or meter repairs.

Pending Table Activation

The “Pending Table” is where the meter stores firmware downloaded over the network. The “Pending Table Activation” event indicates that the meter activated the firmware in the pending table. It means one of the firmware versions in the table is now in use [source: email from AMI team].

DDR could monitor such events to detect malicious meter modifications by correlating them with other auxiliary information such as scheduled firmware downloads or meter repairs.

Pending Table Clear

The “Pending Table” is where the meter stores firmware downloaded over the network. The “Pending Table Clear” event means the meter either activated the firmware successfully and is clearing the pending table, or received a command from the OpenWay Collection Engine to exit firmware download prior to activating firmware in the pending table [source: email from AMI team].

DDR could monitor such events to detect malicious meter modifications by correlating them with other auxiliary information such as scheduled firmware downloads or meter repairs.

C12.22 Deregistration Succeeded

The “C12.22 Deregistration Succeeded” event is generated when a meter de-registers from the DCE. [source: email from AMI team].

DDR could monitor such events to detect malicious meter deregistrations by correlating them with expected or scheduled meter deregistrations.

HAN Meter Network Change

HAN Meter Network Change (with an argument of network restart) normally occurs once daily. Radios are reset daily as a work-around to prevent lockups. [source: AMI vendor representative, at meeting with AMI team].

Most of the HAN events are not of interest to LADWP at present and can be safely ignored, except the “HAN Meter Network Change” event which can be used as a heart beat to infer meter health by DDR [source: meeting with AMI team].

Primary Power Down

The “Primary Power Down” event is generated when the power is shut off to the load (residential/industrial) being monitored by the meter. This event by itself does not necessarily indicate any security threat, but when correlated with security-related events and/or meter configuration events, it might be indicative of malicious activity. It is quite possible that in some situations, a power down event might be the only indication of a successful denial of service attack against a customer. DDR could correlate such events with other auxiliary information such as customer status, scheduled meter upgrades and repairs to infer potential DoS situations.

Primary Power Up

The “Primary Power Up” event is generated when power is restored to the load (residential/industrial) being monitored by the meter. This event by itself does not indicate any security threat, but when correlated with security-related events and/or meter configuration events, it might be indicative of malicious activity. Further, consecutive sequences of Power Up and Power Down events might be indicative of power problems at the meter. DDR could also correlate a power up event with other auxiliary information such as customer status to infer situations where a non-bill-paying customer circumvented a power turn off by the utility.

VoltHour Events

These events are not interesting from a security point of view, but if they occur on a frequent basis they might be indicative of problems in the distribution system. [source: meeting with AMI team]

Events in this category include:

VoltHour Restored From Above Threshold to Normal

VoltHour Above Threshold

VoltHour Restored From Below Threshold to Normal

VoltHour Below Threshold

Volt(RMS) Events

These events are not interesting from a security point of view but if these events occur on a frequent basis they might be indicative of problems in the distribution system. [source: meeting with AMI team]

The events that are generated include:

Volt (RMS) Above Threshold

Volt(RMS) Restored From Above Threshold to Normal

Volt(RMS) Below Threshold

Volt(RMS) Restored From Below Threshold to Normal

Here is a description of when these events are generated (source: email from AMI team member):

As part of the meter's configuration program, the voltage gets monitored to generate Events if "sag" or "swell" of voltage happens, which is when voltage drops or exceeds +/- 20% of nominal voltage (120volts). The percentage boundaries are configurable values. Voltage event gets registered as part of the DataArrived file that is received from meter with every scheduled interrogation or on-demand read. (source: email from AMI team member)

Loss of Phase Error

The "Loss of Phase Error" event is generated when there is error in supply from one of the phases. These events are not interesting from a security point of view, but if these events occur on a frequent basis they might be indicative of problems in the distribution system. [source: meeting with AMI team]

Load Voltage Present

The "Load Voltage Present" event is an important event with respect to energy theft, especially if the reason given in the event is: "Connect failed because load voltage was already present". A meter generates this event if it detects that a voltage was present before it performs a remote connect. Normally, a disconnected house should not have any load voltage present. However, if somebody was diverting power from other sources, a load voltage would be detected. This is a serious event and DDR must alert for the reason specified. [source: meeting with AMI team].

Demand Reset Occurred

In the LADWP system, around 960 meters are demand meters, normally used by larger customers. A LADWP meter reader resets the demand before he leaves the premises. The "Demand Reset Occurred" event is generated, and reports the maximum demand per meter. Around 960 events every two months are expected to be generated as a result. [source: meeting with AMI team] These events are not interesting from a security point of view, but DDR could monitor deviations from the expected reporting frequency, and flag potential violations. Such violations may be indicative of potential problems with the meters, or malicious activity.

Billing Data Cleared

A meter's billing data can be cleared by someone with access to the meter using vendor-provided software. For example, the billing data is reset after the testing of a meter. The "Billing Data Cleared" event is generated whenever the billing data is cleared [source: meeting with AMI team]. If such an event occurs in conjunction with other security-related events, it may be indicative of energy theft attempts.

SiteScan Error

The "SiteScan Error" event is generated by polyphase meters. Every polyphase meter has a specific operation voltage. This exception generated when the meter detects a deviation from the normal voltage [source: meeting with AMI team]. These events are not interesting from a security point of view, but if these events occur on a frequent basis they might be indicative of problems in the distribution system.

Meter Test Mode Events

Meter test mode events are generated whenever a meter is put in test mode by a technician. Meter usage readings generated when a meter is in test mode must be ignored by DDR. Events Include "Test Mode Started" and "Test Mode Stopped".

IPS Events Analysis

Intrusion Prevention System (IPS) events are forwarded by the LADWP ITS team from their McAfee IPS appliances to DDR. Preliminary analysis aimed to correlate IPS information with smart grid events, by time of occurrence, asset(s) affected, or any other related fields. It was not within scope for the CS team to perform IPS analysis for the larger LADWP infrastructure.

Events with Result Status of "Attack Successful"

A tiny percentage of IPS messages (~1 in 100,000) indicated a result status of *Attack Successful*. The *Attack Name* was always “RDP: Microsoft Windows RDP Server Abnormal Termination”, suggesting a denial of service attack. This does not demonstrate that all other attacks were foiled, but that IPS positively identified the signature of one type of abnormality.

None of the affected systems were on smart grid subnets so we concluded this line of investigation.

Events with Destination of DRAS

The fourth most often attacked system, according to IPS data, was a Demand Response Automation Server (DRAS) machine. On closer inspection, the events had mostly tailed off by June, 2015, with the only significant remainder being an approximately hourly "SSL: Server-Initiated Key Renegotiation". We could not correlate these events with other DDR data sources, and investigation of these events was left to the LADWP enterprise-level IPS response process.

There were 315,731 events from August 29, 2914, to July 7, 2015, roughly ten months. But the total for the single month of June 2015 was 790.

Events with Destination of Smart Grid VLAN (other than DRAS)

Excluding DRAS, as noted above, there were 34,103 events from August 29, 2914, to July 7, 2015 with destinations in the smart grid VLAN. Again, these events tailed off to 1,405 in June 2015, showing improvement over time. Again, investigation of these events was left to the LADWP enterprise-level IPS response process.

Events with Source of Smart Grid VLAN

There were 18,611 events from August 29, 2914, to July 7, 2015, with source IP address inside the smart grid VLAN. Once again, these events tailed off, so there were 722 in June 2015, and only a handful of signature types, none of which could not be correlated with other DDR data flows.

DRAS Events Analysis

The Demand Response team installed a client application on one of their DRAS machines to forward Windows Event Log (WEL) events to DDR. There were very few DR application-specific messages in the logs, and the ones present did not provide sufficient information to enable security monitoring of DR at the application level. The bulk of the messages appeared to be standard Microsoft Windows events such as "An account failed to log on", "Checking for Group Policy...", and so on. Further analysis of the currently available data was not warranted. Should security-related monitoring data become available from DR at the application level in the future, we would analyze it. If feasible, we would then implement DDR monitoring and detection of DR security-related events.

EV Events Analysis

The Electric Vehicle (EV) team installed a client application on their web server to forward Windows Event Log (WEL) events to DDR. No data specific to EV applications was found. Further analysis of the currently available data was not warranted. Should security-related monitoring data become available from EV at the application level in the future, we would analyze it. If feasible, we would then implement DDR monitoring and detection of EV security-related events.

SIEM Architecture

The LADWP smart grid SIEM implementation uses two main types of security event feeds, or log sources: DDR security alerts, and classic security events. The top-level architecture of the SIEM system is shown in Figure 1-7.

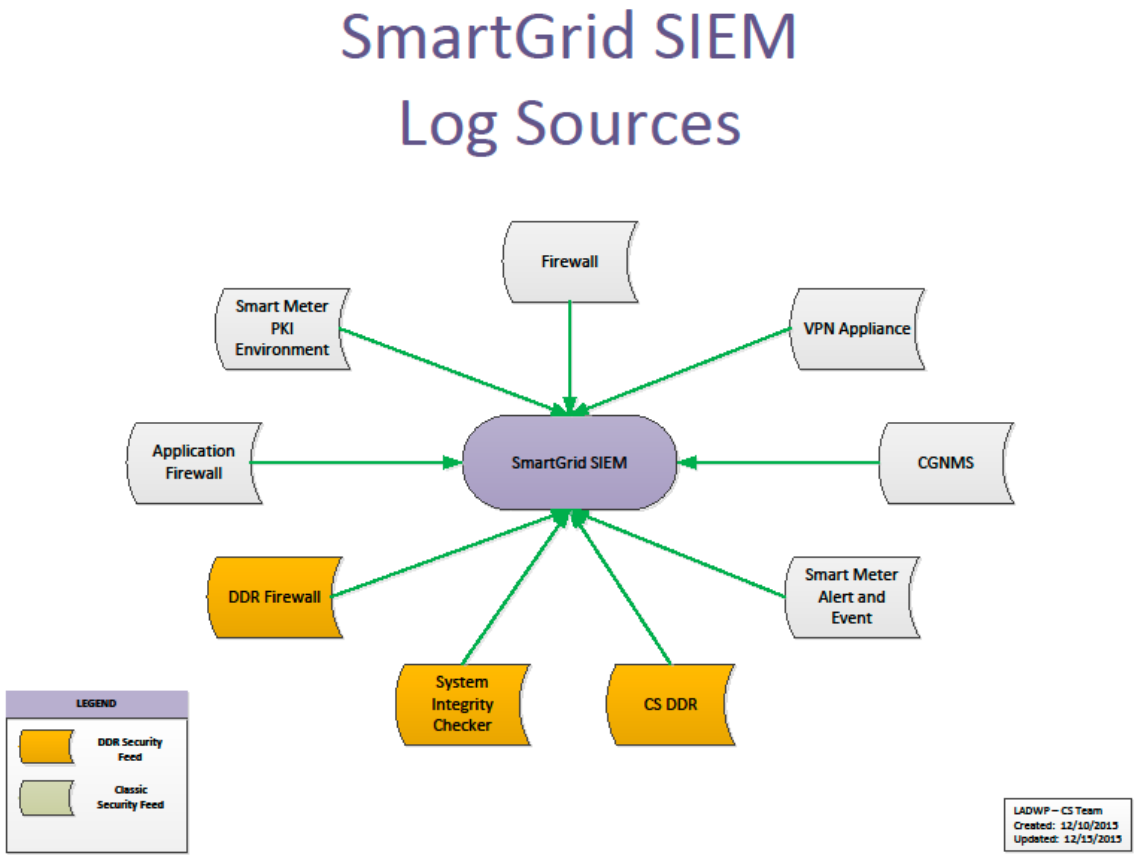


Figure 1-7: Smart Grid SIEM Log Sources

DDR Security Alerts

The DDR system, as described in Sections 0 and 0, provides alerts based on current business processes and the established baseline within the LADWP environment. The DDR detector and diagnostician banks write events to the DDR database. The DDR emitters in turn monitor and forward alert events to the SIEM for the purposes of logging, visualization, and reporting.

The types of DDR events currently being consumed and visualized by the SIEM include: energy theft, denial of service, mass meter disconnects, system integrity events, and DDR firewall alerts.

Classic Security Events

The LADWP SIEM system also consumes raw security events from classical security systems such as firewalls, VPNs, the smart grid public key infrastructure (PKI) system, smart grid communications systems, and application firewalls. SIEM logs these data feeds and visualizes them on the SIEM dashboard. Additionally, correlation rules are being developed to match these raw events to LADWP's business processes and unique environment. SIEM is also using these raw events to provide performance and system stability information to management on a monthly basis.

Demonstration Scenarios

Three sample scenarios that demonstrate the detection and diagnosis of security-relevant events within the LADWP smart grid are described in this section. These scenarios are described as if they would be in a live demonstration.

The correlation of these scenarios with the use cases defined by the National Electric Sector Cybersecurity Organization Resource (NESCOR) is also described. The NESCOR use cases can be found at: http://smartgrid.epri.com/Repository/Repository.aspx

The scenarios were implemented using the algorithms described in Section 0.

Energy Theft Scenario

Description of scenario

In this scenario, we demonstrate how DDR detects potential energy theft attempts, which can be manifested by tampering with the AMI meter, and recalibrating the usage reading using authorized vendor software. The recalibration essentially changes charging or reporting parameters causing low usage to be reported.

Correlation to NESCOR Use Cases

This scenario relates to NESCOR use cases AMI.4, AMI.23, AMI.25, AMI.27, and AMI.30. Each of these NESCOR use cases describes a specific vulnerability in the AMI meter used to realize the threat. AMI.32 describes how power can be stolen using local access via optical port.

Demo Design

Due to operational constraints on performing the demo in near real time (*i.e.*, within minutes or a few hours of the transmission of the suspect usage data), we chose to use historical data collected from the AMI meters to perform this demo.

The demo involves the following steps:

We chose a meter that showed suspiciously low-usage readings in its daily consumption profile. As shown in Figure 1-8 below, this meter started reporting zero values around end of December 2014.

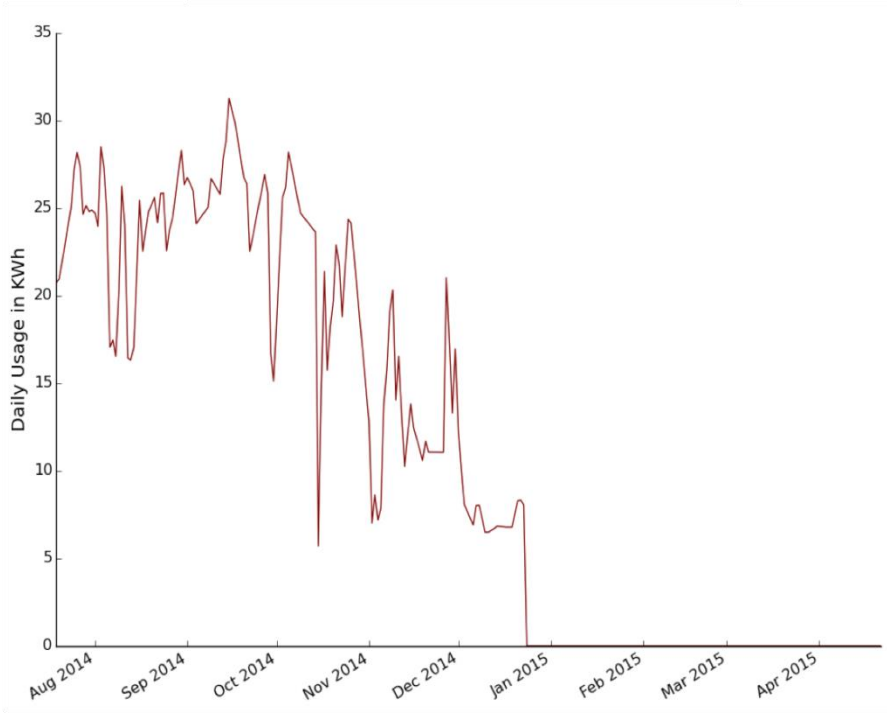


Figure 1-8: AMI Meter Reporting Zero Power Consumption

For the demo, the detector for this scenario (as described in Section 4.1) is temporarily configured to run only for this particular meter ID (to allow to the detection to take place in a few minutes).
On execution, DDR detects and reports energy theft in two stages:
By detecting low usage in reported AMI usage readings
By correlating the low usage alert with other meter alerts
DDR outputs a *Potential Energy Theft Attempt* alert, with an anomaly description as "Zero usage detected and correlated with meter tamper events".
The generated alert is sent to the SIEM for display to the operator.

CGR Unavailability (DoS) Scenario
Description

In this scenario, we demonstrate how DDR detects unavailability of a CGR (perhaps due to a DoS attack by an attacker using a jamming device).

A DoS attack against a CGR will not necessarily bring down a CGR but rather affect the latency of the reads, and cause failed reads. Thus we cannot always rely on information from the CG-NMS (events) to detect CGR issues. In this scenario, we demonstrate that DDR can detect DoS against a CGR by correlating multiple failed reads from meters located behind a CGR. A future extension of this work would be to consider performing detections based on detecting deviations in the response latencies for meters behind the CGR (if this can be instrumented within the AMI network infrastructure).
Correlation to NESCOR Use Cases

This scenario relates to the NESCOR use cases AMI.6 and DR.1.

Demo Design

Due to operational constraints in performing the demo in near real-time, we chose to use historical usage data collected from the AMI meters to perform this demo.

The demo involves the following steps:

Based on available meter-CGR topology, we choose a CGR and the AMI meters connected behind the CGR. Further, we choose a period of time that has known CGR outages.
During the demo, detectors for this scenario (as described in Section 0) are configured to run only for the chosen CGR and associated meter IDs. Further, we set the time period between July 2015 and November 2015, which restricts processing of data to only the said range. These constraints are applied only to ensure that the detection can be performed within a few minutes.

On execution, DDR detects and reports CGR unavailability in two stages
By detecting consecutive meter reporting failures, and
By correlating the meter reporting failures to a particular CGR.
DDR outputs a set of *CGR Unavailable* alerts, with an anomaly description as "*n*% of meters unavailable for CGR *R* on date *T*", and a severity value which is set based on the value of X.

The generated alerts are sent to the SIEM for display to the operator.

Mass Remote Disconnect Scenario
Description

In this scenario, we demonstrate how DDR detects a mass remote disconnect attack, launched to disconnect a large number of AMI meters in the smart grid. A privileged user could initiate malicious disconnects from AMI DCE to disconnect power to a large region of customers causing significant (X%) load drop in the grid within a small amount of time.
Correlation to NESCOR Use Cases

This scenario relates to NESCOR use cases AMI.1, AMI.9, AMI.13, and AMI.31. Use cases AMI.9 and AMI.13 are variations on AMI.1. Use case AMI.31 describes a specific way to manifest this threat by mass compromise of meters with malware.
Demo Design

Exercising the above scenario requires the ability to send remote disconnect to (and get exception messages from) a significant fraction of the meters deployed on SGRDP. Given the limitations on performing this scenario in real time, and on the real system, this demo was performed in two phases (refer to Figure 1-9 below).

Phase 1 (Analytical modeling): This phase (shown as the red boxes in Figure 1-9 below) was performed prior to the demo, and was described under Section 5.1. The output of this phase was an analytical model of the AMI network latencies.

*Phase 2 (Inject simulated exception data and detect mass meter disco*nnect: This phase (shown as the blue boxes in Figure 1-9 below) was performed during the demo.
Given a set of user inputs, such as the number of remote disconnect messages to send, and the meters to send these to, an injector process used the analytical model developed in Phase 1, and generated "remote disconnect success" exceptions. The generated exceptions mimic the temporal profile of the exceptions as generated in the real network.
DDR correlated the occurrence of "remote disconnect exceptions" from a large number of meters within a short span of time, and raised an alert.
The generated alert was then sent to the SIEM.

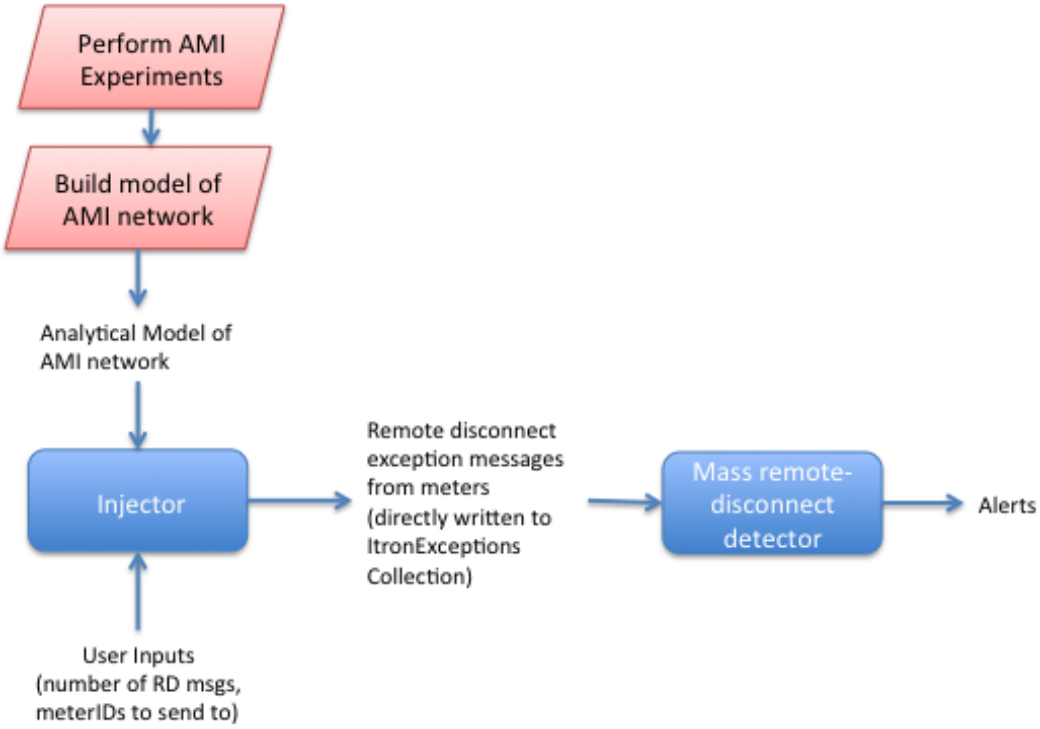


Figure 1-9: Flow for Mass Remote Disconnects Scenario

SIEM Scenario

In this scenario, we elaborate on how the SIEM system supports the three DDR scenarios described above. The SIEM consumes events from the DDR system, as well as classic security events, and displays them on two different SIEM dashboards. This provides near real time visual notification to operations staff who are monitoring the health and security of the smart grid environment.

In our current design, SIEM does not proactively make changes to systems in the operating environment. Rather, operators monitoring the SIEM alerts drill down into specific details to investigate the many raw events that contribute and trigger the DDR alerts. Operators may also use this information to cross-reference with other systems, such as the Work Management System, to identify any false positive alerts due to operational activities (meter deployment, maintenance, planned outages, etc.).

Figure 1-10 and Figure 7-4 shows two key SIEM dashboards being used to support the smart grid.

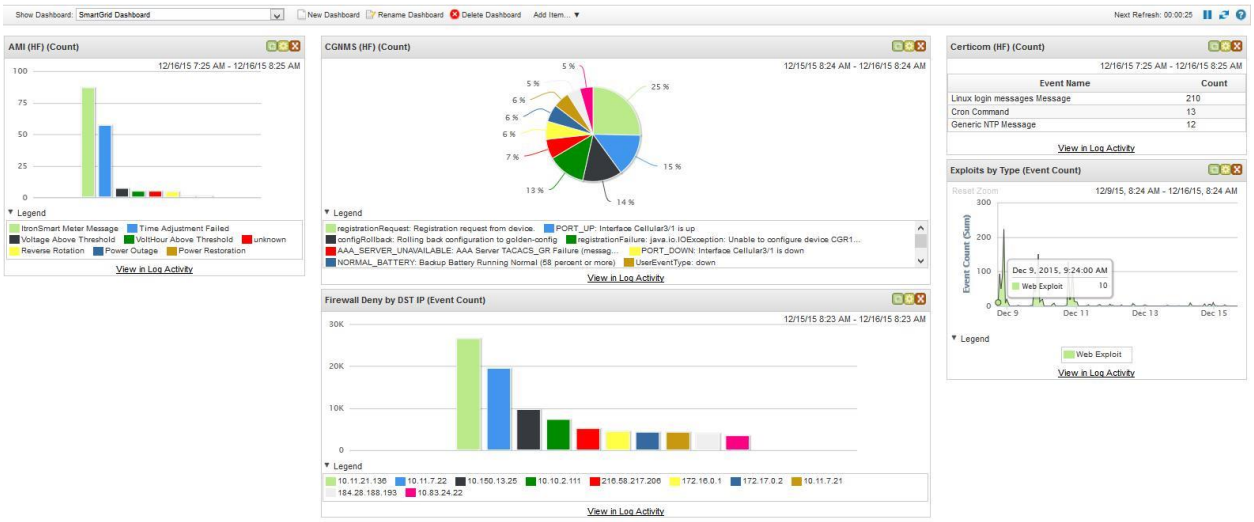


Figure 1-10: SIEM Dashboard for the Smart Grid Displaying Classic Security Events

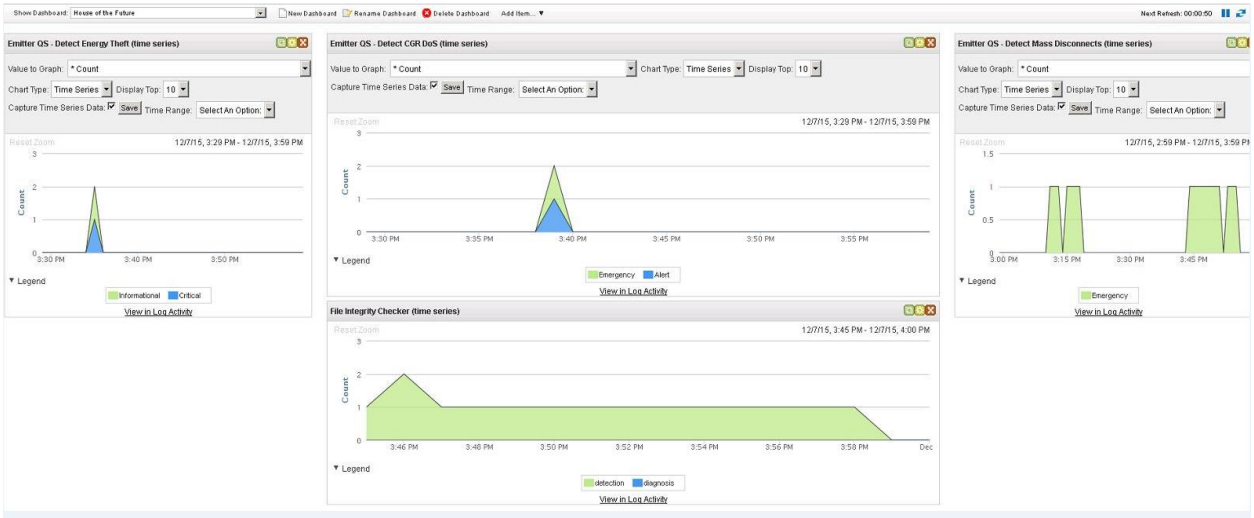


Figure 1-4: SIEM Dashboard for the Smart Grid Displaying DDR Events

Lessons Learned and Recommendations

General and Programmatic Lessons Learned and Recommendations

Program-Level System Engineering

System engineering must be incorporated into the overall program. This is necessary to establish, among other things: a detailed, integrated architecture for the overall program's system of systems; a systematic allocation of requirements and functions; systematic cross-element technical trade studies; processes for the identification and resolution of system-level technical issues; inter-element interface engineering and documentation; and system-level identification of, and planning for, inter-component dependencies. The lack of any significant, sustained systems engineering effort resulted a program that

was implemented as set of isolated “stove-piped” projects. It also had other consequences, some of which are described in subsequent sections.

Program-Level System integration

System integration activities must be incorporated into the program early, and continue through program-level system testing. The lack of a program-level system integration function meant that the melding of individual systems developed by program elements into an integrated whole was problematic. There were no significant program-level integration resources, integration planning, or system-level integration or testing activities. In particular, it would have been helpful to identify early in the program a prioritized set of cross-program operational scenarios (or use cases) to guide the design, integration, and testing of the overall system.

The lack of program-level system integration had many negative consequences for cyber security, including ongoing difficulties in obtaining the data needed from other program elements to enable security detection and diagnosis functions.

Program-Level System Testbed

The lack of a program-wide integrated system testbed (containing all the required hardware and software for all program elements) meant that it was: difficult to identify inter-element technical issues early; not possible to integrate or test individual program elements in a realistic, integrated, test environment; not possible to exercise and evaluate off-nominal behaviors (attacks, faults) without harming the operational system; etc.

The lack of such a testbed was a particularly acute problem for cyber security, since it precluded deliberately introducing simulated attacks in a controlled, non-operational environment in order to evaluate detection, diagnosis, and remediation capabilities.

Modeling and Simulation

Our research work on simulation and analysis of attacks on the smart grid demonstrated the need for a multi-layered, integrated modeling approach to enable accurate evaluation of such complex, heterogeneous, system-of-systems. For instance, consider the case of a cyber-physical attack that originates in the cyber domain, and impacts the physical domain. An accurate analysis of such an attack would require a model of the cyber domain, a model of the physical domain, and more importantly a model of the cyber-physical interface that allows the attacks to propagate across the cyber-physical interface.

Planning for Operations

It is important to design and implement the project with an eye to operational deployment. This means that areas such as maintenance processes, exception handling, code documentation etc. should be clearly addressed to lay the groundwork for a smooth transition to operations at the end of the project. In retrospect, this topic received insufficient attention.

The operational scenarios (or use cases) mentioned above would also have contributed to a focus on operations.

Data Flow Tools and Processes

Given the complexity of, and operational restrictions within, the utility's environment, tools and processes that support the mapping of data flows through that environment – both during design and during integration and testing – are invaluable in assessing risk as well as in designing the defensive architecture. For example, identifying and understanding the nature of various intermediate nodes that data must flow through (e.g., data power devices, firewalls, dmzs, routers etc.) would enable the identification of possible interception points for a man-in-the-middle attack when assessing risk.

Data Management – General

It is important to pay attention to the architecture, processes and principles behind the storage and backup solutions for the handling large datasets. Specifically, here are some issues that should be clearly addressed: accessibility and access control; resource allocation; processing diverse, non-homogenous data; and requirement changes between the development and operational environments.

Avoidance of High-Risk Communications Protocols

The use of a full-duplex, bidirectional, always-on communication protocol (such as Web Sockets) as a communications mechanism should generally be avoided, or at least carefully evaluated, in this type of environment.

At one time such a protocol was considered for use by a program element. Our initial risk assessment of such mechanisms revealed several concerns, some of which are:

The "always on" nature of such protocols means that servers need to keep an open connection to millions of clients, which clearly poses scalability and security risks. For example, a massive DDoS attack can be launched against the utility servers from millions of clients sending arbitrary data on the open connections;

Further, such protocols perform a one-time authentication of their clients while establishing the initial connection, and clients and servers are free to exchange any messages thereafter. This feature allows malware compromising the home-service gateways to easily hijack the authenticated session to send arbitrary data to the server (e,g., spoof DR acknowledgements), or intercept and manipulate the data coming from the server (e.g., perform lower-than-requested load reduction).

Cyber Security-Related Lessons Learned and Recommendations

Building Cyber Security into the System from the Outset

It is important to address cyber security across all system elements from the outset of a program, and continue to do so throughout the system development life cycle. While that was the stated intention and plan within this program, it occurred only to a limited extent. Many factors contributed to this, included those mentioned above (e.g., lack of program-wide system engineering, system integration, and a system testbed).

Another contributing factor was that the element-level development teams were primarily focused on developing and delivering the functionality (e.g., demand response capabilities) of their systems under schedule and resource constraints, and often viewed work on cyber security-related aspects of their systems as a low priority. Even the Cyber Security team itself did not pay adequate attention to the security of its systems.

Data Sources

Under most circumstances, the CS function for a complex system should obtain local copies – possibly redacted, anonymized, and/or summarized – of all the key dynamic, operational data flows in the system being protected. This is necessary to enable the correlation of events among data sources, and to provide independent monitoring of the data integrity of data flows. Ideally the data copies would be transmitted to the CS function out-of-band from the normal system data flows to reduce their vulnerability to attacks and failures within the nominal transmission channels.

Personally identifiable information (PII) and other sensitive data should be anonymized so that its vulnerability to disclosure is not increased by storing in multiple places. However, the anonymizing processes need to produce reliable, non-sensitive data identifiers or keys consistently. For instance, the CS function does not need to know to whom meter usage is being billed or even the "real" meter identifier for a meter, but does need to have a consistent identifier for each meter whether the source of data about that meter is AMI, DR, or some other system. Otherwise, correlation of events from multiple data sources cannot be done.
Data Management for Cyber Security

Often the data flowing into a CS system, unlike other systems, cannot be well characterized in advance. Upstream data sources often change formats over time, based on their own needs and timetables. Also, incoming data may have been deliberately malformed by an adversary, but still must be captured for analysis.

To deal with these circumstances, the approach that the CS system uses internally to manage the data it receives needs to be flexible. A conventional relational database management system is typically not flexible enough for such applications. The use of one of the more recent, *schema-less* (or *no-SQL*) database management systems (DBMSes) can provide the flexibility needed by the CS system. However, the schema-less DBMS must provide adequate performance to handle the potentially large, high-rate data streams that flow into a CS system. Some schema-less DBMSes can be configured to support efficient database write operations, to support high incoming data rates and volumes.
Data Processing Architecture

CS systems often use data collection agents, programs that are responsible for collecting raw data from various data sources for storage and analysis by the CS system. It is valuable to locate the CS data collection agents close (in a network sense) to the data sources themselves. These local agents can perform a number of functions useful to CS, depending on requirements: local data buffering, which can provide some protection against (possibly malicious) network outages; initial data summarization or analysis; local remediation actions, if needed; and encryption and compression of data forwarded to the CS system.

The nature of the data storage, processing and analysis functions performed inside the CS system often lend themselves to a system architecture that is partitioned into distinct stages or phases. An illustrative (but not definitive) set of stages is:
Raw data capture: Incoming data is captured efficiently and stored, with little or no modification.

Initial processing: Stored raw data undergoes basic validation, standard meta-data is added, and the data is stored and split into separate data collections as needed. Unxpected and malformed data are preserved for analysis.
Event detection: Individual pre-processed data collections are analyzed to detect, store, and report events of interest within the stream.
Event correlation, detection, and diagnosis: Events produced from multiple separate data streams are correlated (in time, space, or other ways) to allow the detection and diagnosis of more complex behaviors within the system being monitored.
Remediation: Automated or operator-in-the-loop remediations are executed based on the detection and diagnosis results.
AMI-Related Lessons Learned and Recommendations

The lessons learned are split into three sections: AMI data interfaces, AMI data collection, and AMI data analysis.

AMI Data Interfaces
Interfaces for retrieving CGR-AMI Mapping

The AMI system should provide an application programming interface (API) to retrieve CGR-meter associations. Detection and diagnosis of certain security threats requires us to correlate data from AMI meters and their corresponding CGRs. For example, to infer a Denial-of-Service attack on a CGR would require us to correlate communication failures from meters behind a CGR, and events from a corresponding CGR. This requires the detection and diagnosis processes to maintain a reliable model of CGR-AMI meter associations in the system.

In traditional network architectures, the network topology is often static, and changes only minimally over time. But, in the case of the AMI network, the topology is dynamic and can change frequently, sometimes within a matter of hours. For example, in an AMI network, the routing is dynamic – that is, a meter can switch to communicate with another CGR, or in some cases, to another meter as a relay. For reliable and accurate correlation, the detection and diagnostic processes must thus maintain a dynamic model of CGR-meter associations. The AMI infrastructure should make available API's to retrieve CGR-meter associations easily.

The lack of this ability to obtain the current CGR-meter mapping via an API prevented us from reliably and accurately detecting threats which required correlation between CGR and meter events, or across meter events.
Interfaces for measuring AMI Network Latencies

The AMI infrastructure must provide debugging and diagnostic interfaces (preferably in the form of API's) to easily measure the network latencies in the AMI network. The ability to measure network latencies in a dynamic network is a fundamental tool in the arsenal of a network engineer, and is invaluable for modeling dynamic network behavior for higher-level cyber security reasoning. A lack of this functionality resulted in usage of crude and error-prone techniques for inferring network latencies, subsequently resulting in low-fidelity network models.
AMI Data Collection and Storage
Measuring and Storing Timestamps

Timestamps within data records should be always measured in Coordinated Universal Time (UTC), and stored in a widely accepted standardized representation format such as ISO 8601. UTC is a basis for all local times worldwide, and ISO 8601 is a standard for encoding date, time, time zones and DST information in a standardized format. Doing so allows analysis programs to interpret the data consistently and reliably, and vastly simplifies the handling of time in analysis code.

A mistake typically made is to measure time in local time, and store the time along with time zone information. However, in a distributed system which might span time zones, this complicates the processing of records significantly. Measuring and storing time in UTC allows one to convert the UTC time into local time later, however the reverse is not true (for example, see the discussion at http://pytz.sourceforge.net/#problems-with-localtime).

AMI Data Analysis
Understand semantics of AMI events and exceptions

AMI data analysis must include understanding the detailed semantics of AMI events and exceptions, as relevant to a particular utility's environment. AMI events, exceptions and usage data carry a wealth of information that can be used to infer the state of the AMI meters in particular, and the overall AMI network in general. Although the AMI vendors provide documentation about the events, a utility may choose to interpret the meaning of events and exceptions in a way that makes sense in its deployment. We invested a good deal of effort up front in understanding the semantics of each generated event by collaborating with relevant folks at LADWP. For each event that we observed, we documented the conditions under which a particular event or exception was generated and what it meant to LADWP, along with its importance. This process allowed us to build a knowledge base to tune our detectors and diagnosticians to ignore irrelevant events, weed out false positives, and produce results relevant to LADWP.

For example, we discovered that the event "Reverse rotation detected" indicates a security issue only if it is generated by a non-solar meter. Similarly, the event "Inversion tamper" may not represent a security threat because the deployed meters were either built or programmed in such a way to render reverse rotation or inversion physically impossible.
Using AMI events as auxiliary signals to infer meter health

AMI events that are generated periodically may serve as auxiliary signals to infer the health of the meters. For example, we discovered that the "HAN Meter Network Change" event (with parameter "network restart") was reliably being generated once per day by each meter because of the way the meter radios were being reset once every day. This observation provided a simple way for analysis programs to infer the current health of a meter without invoking a resource-intensive query.
Applying simple pattern recognition over AMI data

AMI data analysis should include the application of simple pattern recognition over AMI events and exception data. For instance, we applied patterns to look for events which were being generated periodically, and we discovered a few meters which were generating the "Reverse rotation detected" event almost 20 times every day, for almost a year. We reported this finding to the AMI team, and on further investigation by field technicians, the meters were discovered to be faulty. Similarly, we

discovered that looking for simple patterns such as “long sequences of zero readings” or “consecutive meter reporting failures” in AMI meter usage data can be used to infer problems such as “potential energy theft”, or “meter communication failures” respectively.

Correlating sequences of AMI events

AMI data analysis should include the correlation of sequences of AMI events, which has the potential to reveal larger underlying problems with the meters, and assist in making more reliable conclusions than would analyzing single events. For example, a sequence of “power down” and “power up” events in succession may indicate a faulty meter. Similarly, a combination of “configuration change events”, along with security events can be used to more confidently establish meter tampering.

Diagnosing AMI usage data anomalies using AMI events

AMI data analysis must include using AMI events to diagnose the cause of anomalies observed in AMI usage data. This enables weeding out of false positives, and increases the accuracy and reliability of detections. For instance, AMI events can be used to diagnose the cause of a “long sequence of zero readings” observed in AMI usage data from a meter. If there are power down events surrounding this observation, then one can conclude that the long sequence of zeroes was due to meter being powered down. Whereas, if there were meter tamper events, then one may conclude that the zeroes reading were potentially due to an energy theft attempt.

Published Papers

Here are the three published papers which include JPL authors. (Papers solely by non-JPL members of the CS team are itemized in other documents.)

Anas Almajali, Eric Rice, Arun Viswanathan, Kymie Tan, Clifford Neuman. A Systems Approach to Analyzing Cyber-Physical Threats in the Smart Grid. In IEEE Smart Grid Communications Conference (IEEE SmartGridComm), Vancouver, Canada, October 2013.

Arun Viswanathan, Kymie Tan, Clifford Neuman. Deconstructing the Assessment of Anomaly-based Intrusion Detectors for Critical Applications. Proceedings of Research in Attacks, Intrusions and Defenses (RAID) Symposium, St. Lucia, October 2013.

Clifford Neuman, Kymie Tan, Mediating Cyber and Physical Threat Propagation in Security Smart Grid Architectures. Proceedings of the 2nd International Conference on Smart Grid Communications (IEEE SmartGridComm), Brussels, October 2011.

Appendix: Acronyms

Acronym	Meaning
AMI	Advanced Metering Infrastructure
CG-NMS	Connected Grid-Network Management System, part of AMI
CGR	Connected Grid Router, part of AMI
CS	Cyber Security
DCE	Data Collection Engine, part of AMI
DDR	Detection, Diagnosis, and Remediation
DoS	Denial of Service, a type of network-based attack
DR	Demand Response
DRAS	Demand Response Automation Server, part of the DR system
DWP	Department of Water and Power
EV	Electric Vehicle
IPS	Intrusion Protection System
ITS	Information Technology Services, part of LADWP
JPL	Jet Propulsion Laboratory
KWh	Kilowatt-hours
LADWP	Los Angeles Department of Water and Power
LPC	Load Profile Channel, a type of AMI meter data
NESCOR	National Electric Sector Cybersecurity Organization Resource
NMS	Network Management System
PKI	Public Key Infrastructure
RD	Remote Disconnect
RTT	Round-trip time
SG	Smart Grid
SIEM	Security Information and Event Management
Vh	Volt-hour
WEL	Windows Event Log
Wh	Watt-hour

Appendix O Basic DDR Component Testing

LADWP Smart Grid Regional Demonstration Program

Cyber Security (CS) Document

Basic DDR Component Testing

Version 1.0

August 31, 2014

This document may provide designs or plans regarding the creation or use of customer-specific information including without limitation billing, usage, location, address and other personally identifiable information (collectively, "Customer Data"). LADWP may collect, create or cause to be created such Customer Data under the designs or plans in this document, but LADWP will not release Customer Data to any other entity, public or private, without strict confidentiality protections binding on the other entity. However, LADWP may release information regarding the aggregate usage, load shape, or other general characteristics of a group or rate classification ("Generic Information") utilizing the Customer Data. No information which might potentially reveal information regarding the identity of any customer will be included in Generic Information. Customer Data is treated as confidential to ensure compliance with all applicable legal and regulatory requirements, including but not limited to California Public Utilities Code Sections

Document Change History

Date	Version	State	Change Description
2014-08-15	0.1	Draft	Initial draft outline
2014-08-31	1.0		Initial release

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Introduction

Document Purpose

The purpose of this document is to describe the Cyber Security (CS) unit (*aka* component-level) testing performed on basic Detection/Diagnosis/Response (DDR) capabilities developed to date. The CS Top-Level Test Plan (dated May 13, 2013) describes the overall test plan and provides a foundation for this document. This document supports item 3.5.4.1 - "Grid resilience against cyber attacks" in the Statement of Program Objectives (SOPO).

Objectives and Scope

This document applies the CS test plan to the functions delivered for basic DDR to date. This document defines the set of unit test activities necessary to ensure that the implemented DDR components meet their intended functionality, and summarizes the results of those tests.

Overview of DDR Capabilities

This delivery implements the underlying infrastructure supporting the CS environment and basic DDR. The system context for CS is shown in Figure 1-11. Customer consumption that is symptomatic of energy theft is used as an example scenario to exercise the set of basic DDR functionality within this delivery and these are:

Collect customer consumption data from the Advanced Metering Infrastructure (AMI).

Store sufficient history of consumption data for each customer to calculate meaningful statistics.

Process consumption data through one or more detection algorithms that identify anomalous consumption behavior.

Write records of detections of anomalies to a permanent store for downstream processing by operators or diagnosis algorithms.

Display detected anomalies and provide status monitoring for CS components with a visual dashboard.

Basic DDR is composed of six component types:

Collector – A software component that provides an interface from a data source into the CS components. As of the date of this report, the following collectors have been implemented:

AMI DCE Collector

AMI CG-NMS Collector

Intrusion Prevention System (IPS) Collector

Demand Response Automation Server (DRAS) System Log Collector

Database – Central database through which all data and events flow. This is the primary integration point for DDR capabilities.

Detector Bank – Container for the set of detection algorithms, provides basic functionality to manage the execution of detection algorithms.

Detector – An algorithm that can be applied to a single data stream to detect incorrect or anomalous values or behaviors. The current detectors are:

Statistical Outlier Detector

Running Average Detector

Temporal Sequence-based Detector

Statistical Chi-squared Detector

Diagnosis – An algorithm that correlates information from various data streams to identify pertinent events. The diagnosis algorithms are:

Rule-based

Hidden Markov Model

Bayesian Model

Visualization – Display of CS component state.

Data flow for demonstration scenario is shown in Figure 1-12. As of the date of this document, diagnosis functions are under development and have not yet been integrated. Integration of the other functions is addressed in the sections below.

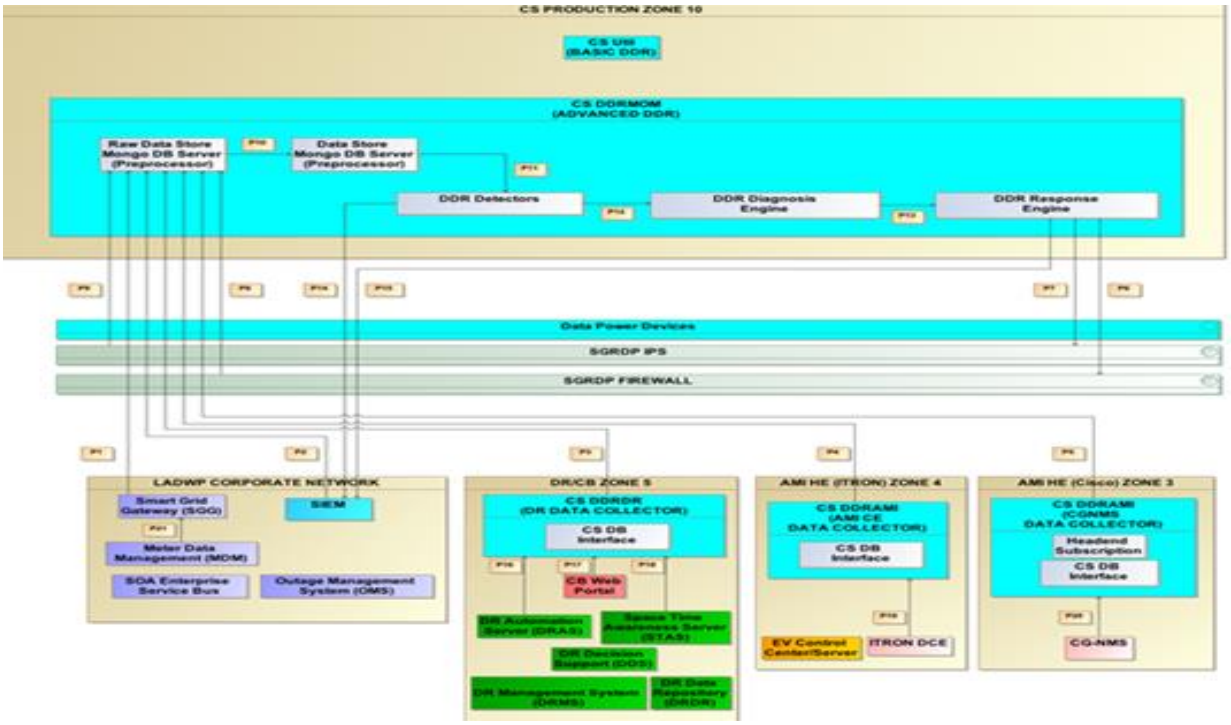


Figure 1-11: CS Context

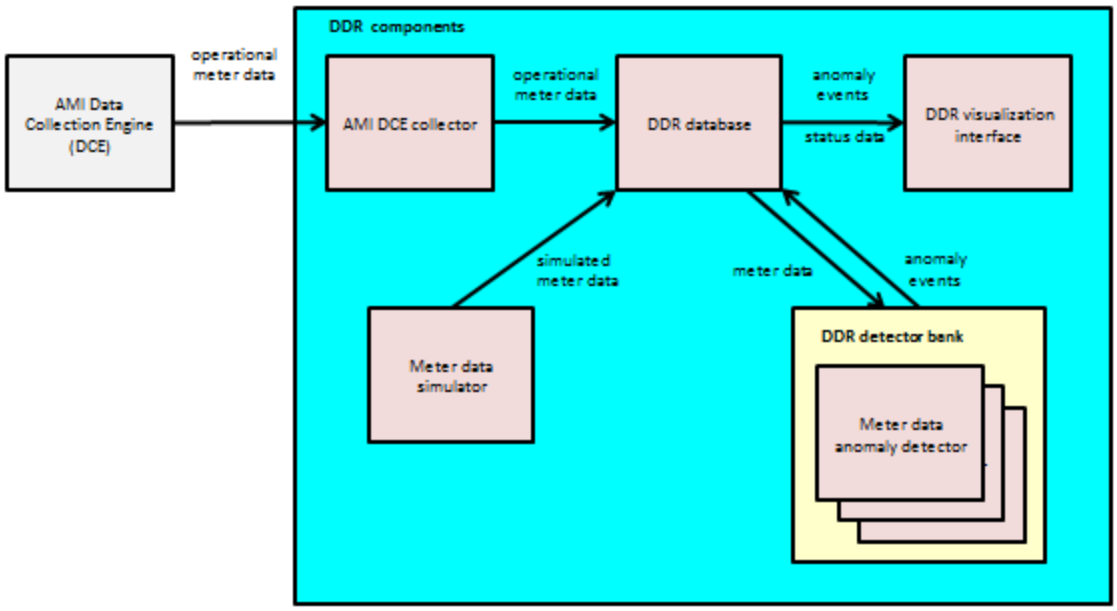


Figure 1-12: DDR Data Flow

Basic DDR Test Activities

The basic DDR test activities are intended to *verify* that the implemented system is capable of collecting and processing AMI data necessary to detect energy theft, and *validate* that the end-to-end system will detect well-defined energy theft cases when they exist in the data stream.

Verification activities are categorized by unit, interface, and test type.

Unit tests, which are summarized in this document, include:

Function: Verify that the unit accepts data, processes it as expected, and produces the expected output.

Performance: Verify that the unit performs its function with the needed speed, accuracy, and error rate.

Interface tests, which are summarized in CS integration documents, include:

Function: Verify that the sender produces output in the expected format; Verify that the receiver accepts input in the expected format; Verify that the channel transmits signals without alteration.

Performance: Verify that the sender produces output at the expected period and rate; Verify that the receiver is able to receive and ingest input at the expected period/rate; Verify that the channel is capable of transmitting data at the required rate with an acceptable latency and error rate.

To first order, only functional tests are necessary to provide assurance that the demo system will integrate well. Performance tests provide additional assurance that the system will operate well within bounded operational scenarios, and allow the extrapolation of performance for scaling.

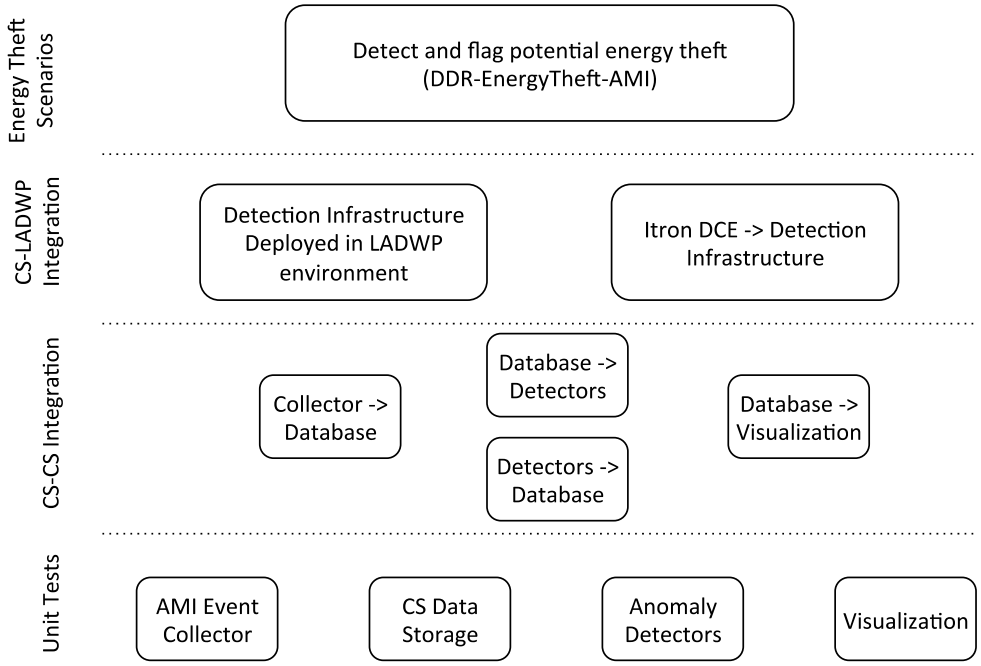
The same pattern can be expanded to apply to units and interfaces as new system elements are implemented. This will include, but is not limited to:

CS-MDM interface

CS-DR interfaces

Structure

Figure 3-1 illustrates the high-level test activities for the Basic DDR delivery. It is intended to map activities for this delivery into the test level definitions defined in Figure 2-1 of the Cyber-Security Top-Level Test Plan. The component test activities addressed here are limited to the bottom tier of unit tests



in the figure. Integration verification at the higher levels is addressed in the document *Integration of SGRDP Detection – Basic*.

Unit Verifications

Unit tests are defined to check that the basic functionality of each component is correct.

Unit-Level Verification Activities:

Verification				
ID	Unit	Test	Description	Method
U1	AMI DCE Collector	Func	DCE Collector processes input from the DCE in the expected format, and correctly transforms it for logging to the event store.	Inspection

Figure 1-13: Verification Levels

		Perf	DCE Collector collects data at maximum and minimum rates from DCE (burst and sustained), writes to output with expected latency, error, and drop rates.	Test
U2	DDR Database	Func	DDR Database logs events from event receiver in the correct format, and provides them to other elements in the correct format.	Inspection
		Perf	DDR Database logs events from event receiver at expected maximum and minimum rates (burst and sustained) with expected latency, error, and drop rates. Event store provides events to event processor at expected rates with expected latency, error, and drop rates.	Test
U5	Meter Data Anomaly Detector	Func	Detector can accept data of the expected format from the event store, and correctly identify expected conditions.	Test
		Perf	Detector identifies anomalous conditions with acceptable latency, hit rate, and false alarm rate.	Test
U6	DDR Visualization Interface	Func	Visualization Interface displays current state of monitoring systems with data from the event store.	Test
		Perf	Visualization Interface events from a maximum number of elements, and correctly displays system status within expected latency and error rates.	Test

U1 – AMI DCE Collector Verification Results

Results: Partial success

Operational data from the AMI DCE is used to flow through the collector and write records in the expected CS format to the correct MongoDB instance.

The AMI DCE collector is able to collect meter data records of all types from the AMI DCE, and reformat the records to the standard CS format for storage in the DDR Database.

The AMI DCE collector is capable of executing at data rates at least as high as the maximum burst rate seen to date from the DCE.

Open Issues:

Currently, CS does not have a clearly stated expectation of maximum possible rate of record generation or data throughput provided by the DCE. The collector can be verified for operation up to the maximum rates seen to date, but not the maximum prospective rate (if different from the recent rates).

Currently, CS does not have a clearly stated expectation of all possible record contents generated by the DCE. By inspection, we can verify that the collector is capable of accepting and parsing the Itron XML record format, but we do not currently have the requirements or resources to verify that all data fields in uncommon records are processed without corruption.

U2 – DDR Database Verification Results

Results: Success

Each database in the DDR MongoDB instance correctly stores records in the provided format, and is capable of returning records on request.

The DDR Database is capable of accepting and storing data from all sources at the volume and rate seen in the deployed SGRDP.

Database rate of growth is within the capabilities of the MongoDB configuration on all CS machines.

The below numbers are pulled from a mix of test and operations to demonstrate the performance of the system. Number are not included to be representative of expected future operations.

Data Volume, by database:

Database	Current Size (MB as of 8/28/14)	Avg Growth Rate (Operations, MB/day)	Max Observed Growth Rate (MB/day)
CS_MDM	80,024	666.3	27,986

Record count, by collection:

Database	Number of Records (as of 8/28/14)	Avg Growth Rate (Operations, Rec/day)	Max Observed Growth Rate (Rec/day)	Avg Obj Size (B)
CS_MDM.ItronEvents	2,194,552	52,129	75,131	1,000
CS_MDM.ItronExceptions	64,138	1,563	5,684	1,008
CS_MDM.ItronData	5,819,753	135,159	197,461	1,008

Sunday, August 3 2014 was a peak load day for the CS databases. On that day, the virtual machine (VM) reported 91% idle CPU and only approximately 30% utilization of memory. This indicates CS systems have significant margin on system performance, even as presently configured.

Open Issues:

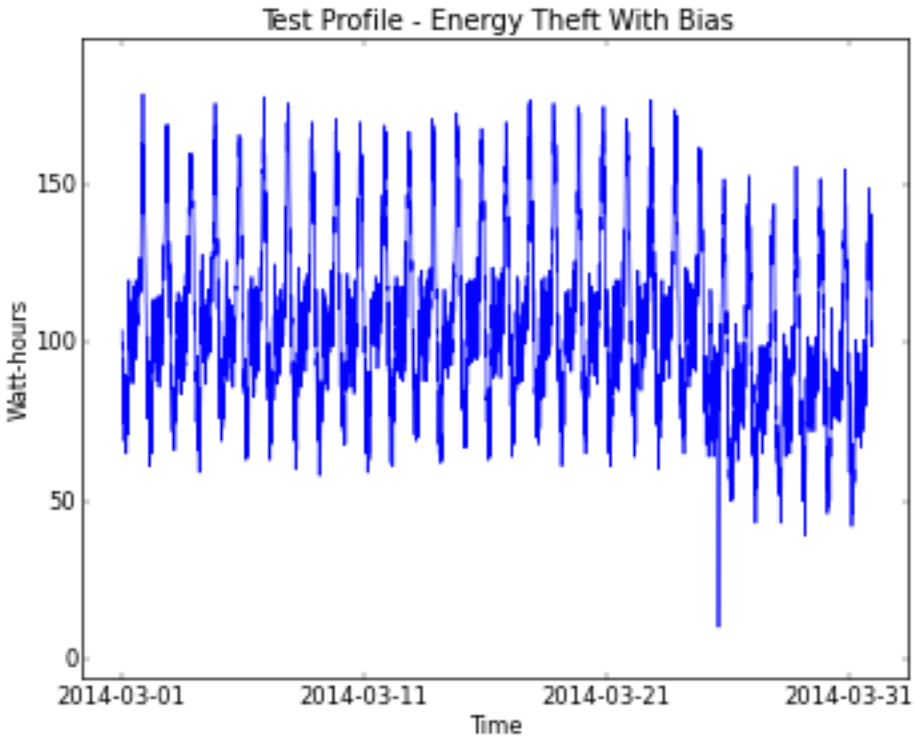
CS had not done a detailed assessment of the database and data storage design with respect to the measured performance. To date, database namespace size has been the only encountered limitation of the MongoDB installation, limiting the total number of records prior to adjustment. Namespace is configurable with a hard limit of approximately 3 million, while CS is currently configured for a maximum namespace limit of 98,000.

U5 - Detector Bank and Detectors

Results: Success

A unit test script "run_detector" ran MDAD repeatedly on exported production data hosted on separate environments (developer laptop, JPL Integration Environment, CS-LADWP Integration Environment) and produced identical output each time. Metrics were also captured on RAM consumed during each run, and total running times. With approximately 3 months' of data, the Detector took about 4 hours to complete, so with 2 years' of data a detection cycle (if not modified) will complete in ~32 hours. This execution time is sufficient to detect anomalies with a large data set, within the applicable response time for energy theft detection. Similar execution times may or may not be acceptable for other classes of anomalies and failures.

A small test set was derived from operational meter data, with a bias applied after an injected fault



(especially low power reading of 10 Wh), as shown in Figure 1-14.

Command-line options are provided to modify the selected defaults for key parameters (such as threshold setting or running-average window size) so that hit rates and false alarm rates can be tuned with experience. Below are shown several different values for each such parameter used in unit testing to demonstrate their effects on hit and false alarm rates.

Detector: Statistical Outlier

Parameter thresh_stdev_factor (default 2.5)	# Alarms	False alarm rate (1 - (1/Alarms))	Closest Alarm to Injected Fault time 2014-03-25T15:00:00
2	183	0.995	2014-03-25T15:00:00

2.5	23	0.96	2014-03-25T15:00:00
3	1	0	2014-03-25T15:00:00
4	0	--	--

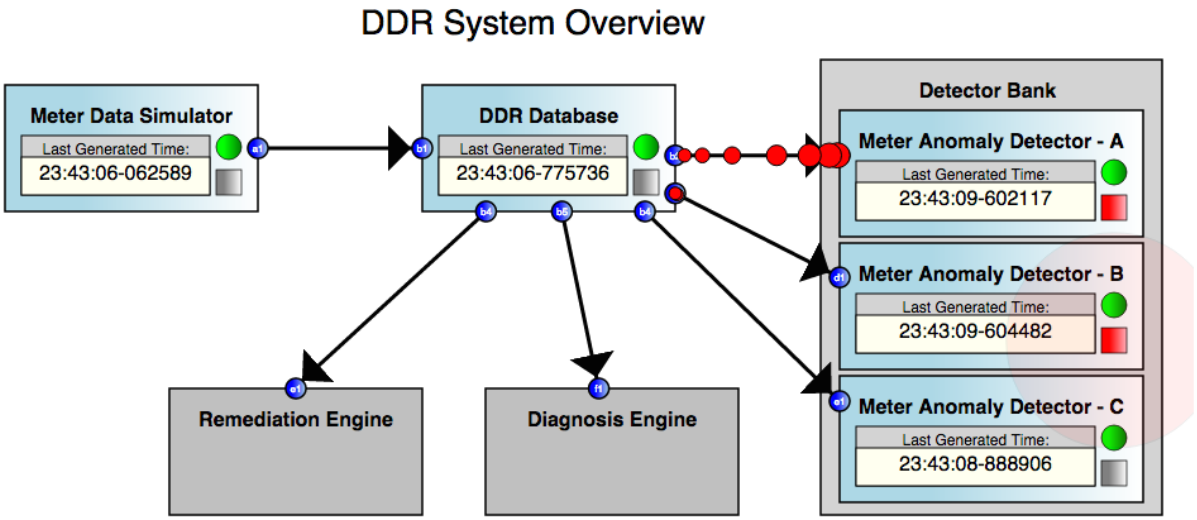
Detector: Running Average

Parameter Window_size (default 96)	Parameter Slope (default 1.5)	# Alarms	False alarm rate (1 - (1/Alarms))	Closest Alarm to Injected Fault time 2014-03-25:15:00:00
96	1.5	0	--	--
30	1.5	45	0.98	2014-03-25T07:45
40	1.5	1	0	2014-03-25T05:15
50	1.5	0	--	--
96	0.4	5	0.80	2014-03-24T15:15
96	0.5	2	0.50	2014-03-24T15:15
96	0.56	1	0	2014-03-24T15:15
96	0.6	0	--	--

Open Issues

Performance – Execution time of the meter data anomaly detectors was long, and resource intensive. While the current deployment has been verified to operate as expected and within reasonable constraints, future functionality may require additional resources and/or optimizations.

U6 – DDR Visualization



Status

Meter ID	Anomaly Time	Anomaly Desc	Originator
9.99.999.9.999999.9.99.999999	2014-03-01T00:45:00	Running average value abrupt change	Meter Anomaly Detector - B
9.99.999.9.999999.9.99.999999	2014-03-01T00:30:00	Running average value abrupt change	Meter Anomaly Detector - B
9.99.999.9.999999.9.99.999999	2014-03-02T22:00:00	Value 157.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-02T21:00:00	Value 167.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-02T20:45:00	Value 169.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-02T20:30:00	Value 161.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-02T20:15:00	Value 157.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-02T19:15:00	Value 161.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-01T21:45:00	Value 160.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-01T21:30:00	Value 160.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-01T21:15:00	Value 160.0 too high with mean 105 and std 25	Meter Anomaly Detector - A
9.99.999.9.999999.9.99.999999	2014-03-01T21:00:00	Value 165.0 too high with mean 105 and std 25	Meter Anomaly Detector - A

Figure 1-15: DDR Visualization

Results: Success

The DDR Visualizer monitors the DDR database for new data and presents a graphic depiction of data flow inferred from the appearance of that data. It refreshs the display in an infinite loop, with approximately 3-5 second refresh time. Red dots between units indicate data flow, one dot per input event. At varying input rates we observed by inspection the corresponding indicator behavior.

Two CS units were used as data generators for the Visualizer to work with. Each has options to throttle the rate at which they output data. Each writes its data to the DDR database, which was presented as a third unit.

The Meter Data Simulator unit was represented as a box, with a green circular dot that flashed when the Visualizer found new data. This was tested at several different output rates: "batch" (output as fast as possible - hundreds of events per second), 1 event every two seconds, and 1 event per second.

- The Detector Bank unit was represented as a box, inside of which were smaller boxes for each individual detector. Each detector's box had a green circular dot that flashed when the Visualizer found new data, and a red square indicating detected events. Additionally, detected events were shown in the status table at the bottom of the visualizer, and were checked by inspection against the terminal output of the detector itself.
- This was tested at several different output rates: "batch" (thousands of events per second), 1 event every two seconds, 1 event per second, and 5 events per second.

Open Issues: None

Appendix P Integration of SGRDP Detection – Basic



Cyber Security (CS) Document

DDR August 2014

Integration of SGRDP Detection – Basic

Version 2.0

Date	Version #	Reason for Change(s)	Author(s)
2014-08-15	1.0	Initial draft outline	JPL CS team
2014-08-31	2.0	Delivered to LADWP	JPL CS team

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INTRODUCTION

Purpose

The purpose of this document is to describe the integration of Cyber Security (CS) detection technologies into the Smart Grid Regional Demonstration Project (SGRDP)/Los Angeles Department of Water and Power (LADWP) environment to date. Some of these basic capabilities were demonstrated for LADWP in June 2014.

The work described in this document maps to SGRDP Statement of Program Objectives (SOPO) item 3.5.4.1 "Grid resilience against cyber attacks".

Objectives and Scope

This document describes both the basic detectors and the deployment infrastructure that has already been delivered.

The delivered software executes within the SGRDP computing infrastructure at LADWP. Figure 2-1 below is the component diagram representing the SGRDP, which provides the context in which the detection and diagnosis operates. The CS components are shown in blue. The lines of communication between the components are also shown.

This document describes the verification of integration of functions in the scope of:

Connections between the Advanced Metering Infrastructure (AMI) Itron Data Collection Engine (DCE) and Connected Gateway-Network Management System (CG-NMS) system and the CS Detection/Diagnosis/Response (DDR) system to obtain AMI meter and network data.

Storage of AMI data in the DDR database.

Detection of real and/or simulated “meter data anomaly” events from the real and/or simulated meter data. These detected events are stored in the DDR database.

Visualization of the detected events and DDR-internal data flow.

OVERVIEW OF DDR CAPABILITIES

This delivery implements the underlying infrastructure supporting the CS environment and basic DDR. Customer consumption that is symptomatic of energy theft is used as an example scenario to exercise the set of basic DDR functionality within this delivery and these are:

Collect customer consumption data from the AMI DCE.

Store sufficient history of consumption data for each customer to calculate meaningful statistics.

Process consumption data through one or more detection algorithms that identify anomalous consumption behavior.

Write records of detections of anomalies to a permanent store for downstream processing by operators or diagnosis algorithms.

Display detected anomalies and provide status monitoring for CS components with a visual dashboard.

Basic DDR is composed of six component types:

Collector – a software component that provides an interface from a data source into the CS components. As of the date of this report, the following collectors have been implemented:

AMI DCE Collector

AMI CG-NMS Collector

Intrusion Prevention System (IPS) Collector

Demand Response Automation Server (DRAS) System Log Collector

Database – central database through which all data and events flow. This is the primary integration point for DDR capabilities.

Detector Bank – Container for the set of detection algorithms, provides basic functionality to manage the execution of detection algorithms.

Detector – An algorithm that can be applied to a single data stream to detect incorrect or anomalous values or behaviors. The current detectors are:

Statistical Outlier Detector

Running Average Detector

Temporal Sequence-based Detector

Statistical Chi-squared Detector

Diagnosis – An algorithm that correlates information from various data streams to identify pertinent events. The diagnosis algorithms are:

Rule-based

Hidden Markov Model

Bayesian Model

Visualization – Display of CS component state.

Data flow for demonstration scenario is shown in Figure 2-2.

As of the date of this document, diagnosis functions are under development and have not yet been integrated. Integration of the other functions is addressed in the sections below.

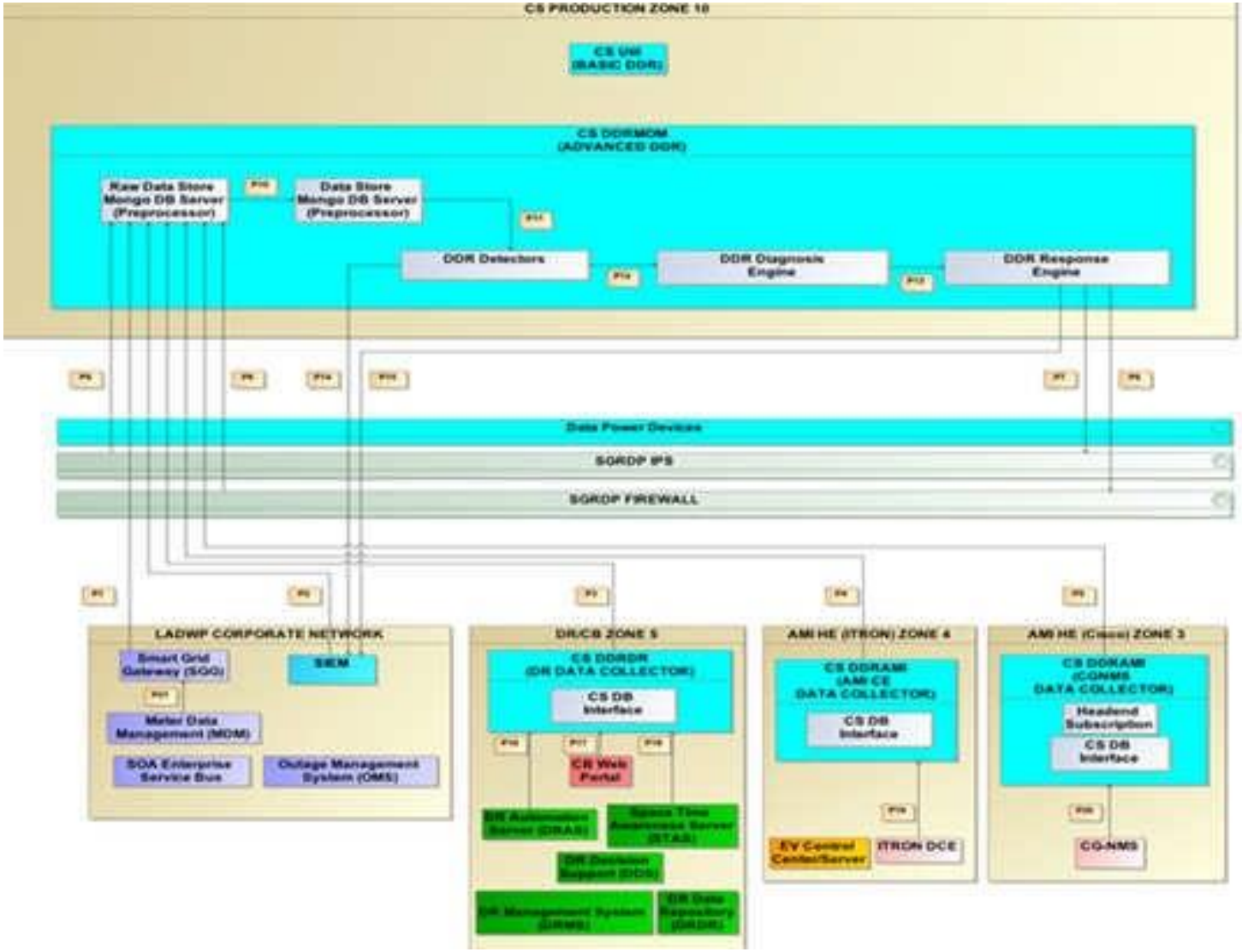


Figure 2-1: CS Context

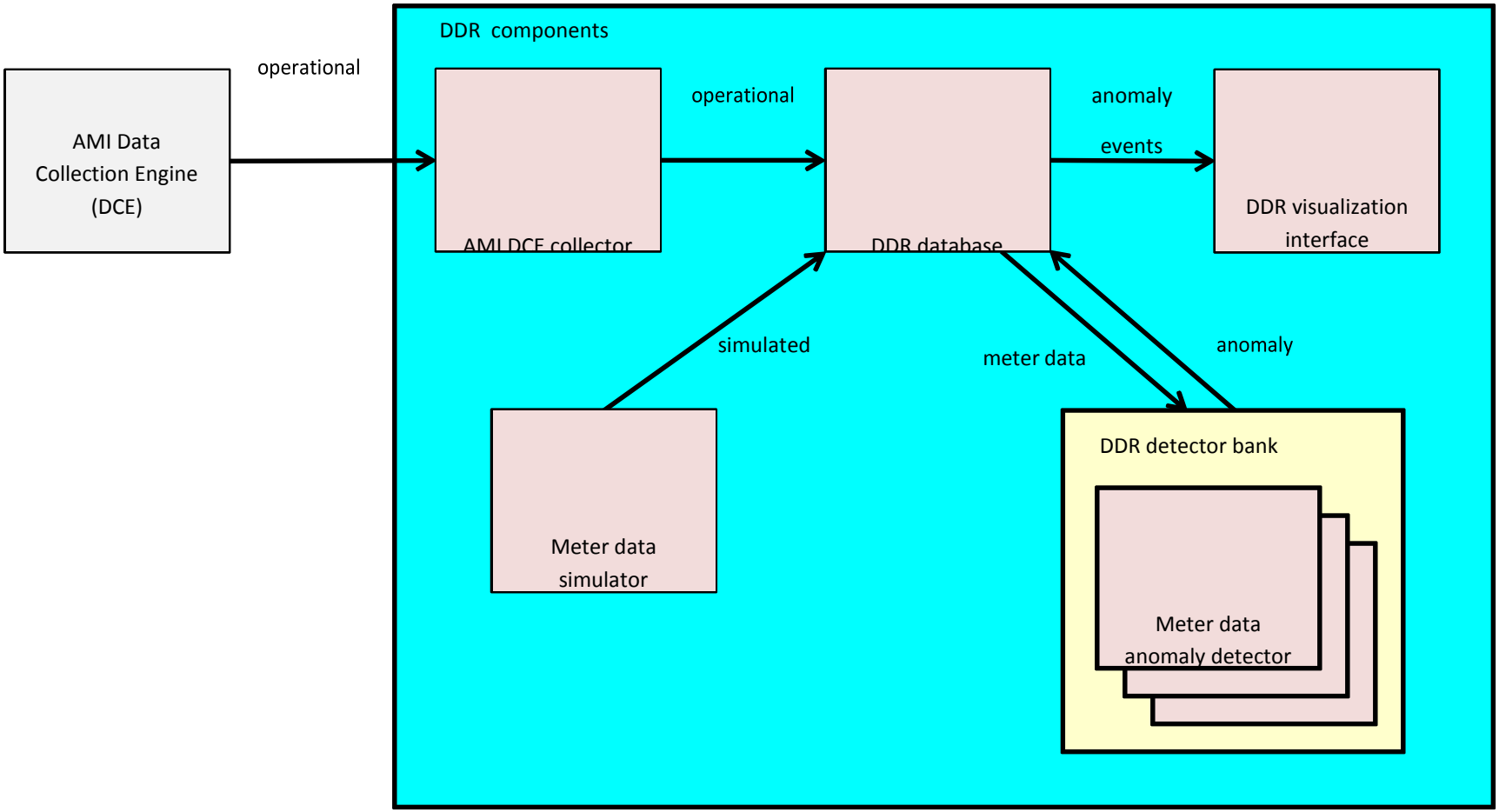


Figure 2-2: DDR Data Flow

Interfaces By Component For Verification

Collectors and Database

A DDR collector is a piece of software that requests data from a data source, receives the data from the source, and writes the data to the DDR database.

AMI-DCE Collector

Description

The AMI-DCE collector receives Web Service data from DCE and saves it to the DDR Database.

Interfaces

Web Service data (XML/SOAP) is received in Apache Tomcat from DCE via a publish/subscribe model. The data is then formatted according to the Event Format (as described in the internal *DDR-Data Collection and Logging Architecture* document) and is stored in individual tables in the collection named CS_MDM in the DDR database (one table per meter).

Software Dependencies

Apache Tomcat 7.0.42 or higher; Apache Axis 2 1.6.2 or higher; JDK 1.7.0_45 or higher

AMI-CGNMS Collector

Description

The AMI-CGNMS collector receives Web Service data from CG-NMS and saves it to the DDR Database.

Interfaces

Web service data (XML/SOAP) is received in Apache Tomcat from Itron-Cisco CG-NMS via a publish/subscribe model. The data is then formatted according to the Event Format (as described in the internal *DDR-Data Collection and Logging Architecture* document) and the formatted data is stored in CgnmsEvents inside the EventStore in the DDR Database.

Software Dependencies

Apache Tomcat 7.0.42 or higher; Apache Axis 2 1.6.2 or higher; JDK 1.7.0_45 or higher

IPS Collector

Description

The IPS collector obtains alerts from the LADWP IPS. IPS sends data via syslog format to a DDR installation of syslog-ng configured to receive it. Syslog-ng is a third-party syslog server used by DDR.

Interfaces

IPS data is sent via syslog format to syslog-ng. Syslog-ng then saves it to a staging table in the DDR database. A preprocessor queries the latest records, formats the results according to the Event Format (as described in the internal *DDR-Data Collection and Logging Architecture* document) and stores the results in the IPSEvents table inside the EventStore in the DDR Database.

Software Dependencies

Syslog-ng 3.4.2 or higher; Python 2.6-2.7.x; PyMongo 2.6.3 or higher; a 2014 release of pytz or higher; supervisord 3.0 or higher

DRAS System Log Collector

Description

The DRAS log collector is intended to collect events generated by the DRAS software using the Windows Event framework.

Interfaces

On the DRAS server, a Snare Enterprise Agent reads Windows Event Logs as they are generated by the DRAS software, converts them to syslog format and forwards them to an DDR installation of syslog-ng configured to receive them. Syslog-ng then saves the data to a staging table in the DDR database. A preprocessor queries the latest records, formats the results according to the Event Format (as described in the internal *DDR-Data Collection and Logging*

Architecture document) and stores the results in the DRASEvents table inside the EventStore in the DDR Database.

Software Dependencies

Snare Enterprise Agent for Windows 4.2.5 or higher; Syslog-ng 3.4.2 or higher; Python 2.6- 2.7.x; PyMongo 2.6.3 or higher; a 2014 release of pytz or higher; supervisord 3.0 or higher

DDR Database

The DDR database is the central repository for data received by DDR, as well as other data generated by DDR internally (e.g., detected events). It is the primary integration point for DDR capabilities.

The DDR database is implemented using the MongoDB database management software. Instances of the database reside on development and production machines at LADWP. Using multiple logical databases, data is staged, formatted, and made available for use by CS DDR algorithms. When a detection or diagnosis algorithm identifies an event of interest, it then writes the event back to a separate database within the DDR Database for later retrieval, analysis, and visualization.

Interfaces

All input and output interfaces are documented with other functional elements.

Software Dependencies

CS functions use MongoDB version 2.6.3 with no special configurations or packages.

Detector Bank

Description

The detector bank is designed to contain a collection set of detectors. The detector bank obtains data (e.g., meter usage data from the DDR database) after which a detector, or combination of detectors, analyzes the data to detect potential events. The infrastructure is designed to be flexible, in that it allows the incorporation of new detection algorithms that may be better suited to new and evolving threat scenarios. The detector bank writes detected events back to the DDR database.

Interfaces

The Meter Data Anomaly Detectors (MDADs) are implemented as Python code, and are started from the Unix command line. Their operation is controlled by a variety of command line options.

Their inputs are meter data, which they extract from the CS_MDM database. Their outputs are events that identify meter data anomalies. Via command line options, detection events may written to the terminal screen, and/or to a configurable database (typically CS_EVENTS or CS_DETECTOR) within the DDR database.

Software Dependencies

Flask 0.10.1, Jinja2 2.7.3, MarkupSafe 0.23, Werkzeug 0.9.6, backports.ssl-match-hostname 3.4.0.2, gevent 1.0.1, greenlet 0.4.2, itsdangerous 0.24, matplotlib 1.3.1, nose 1.3.3, numpy 1.8.1, pymongo 2.7.1, pyparsing 2.0.2, python-dateutil 2.2, pytz 2014.4, six 1.7.2, tornado 3.2.2, wsgiref 0.1.2.

Statistical Outlier Detector

For each meter ID found in the input database, the mean and standard deviation are calculated over all energy usage readings present. A detection is made when any reading is found to be more than a configurable fraction/multiple of standard deviations away from the mean.

Running Average Detector

For each meter found in the input database, the running average over a configurable window size (some number of readings before and after a given reading time) is calculated. A detection occurs when average for a time window is more than a configurable delta from the previous time window's average.

CS LOCALINTEGRATION

CS DDR integration activities occur in several environments. The environments are shown in Figure 4-1

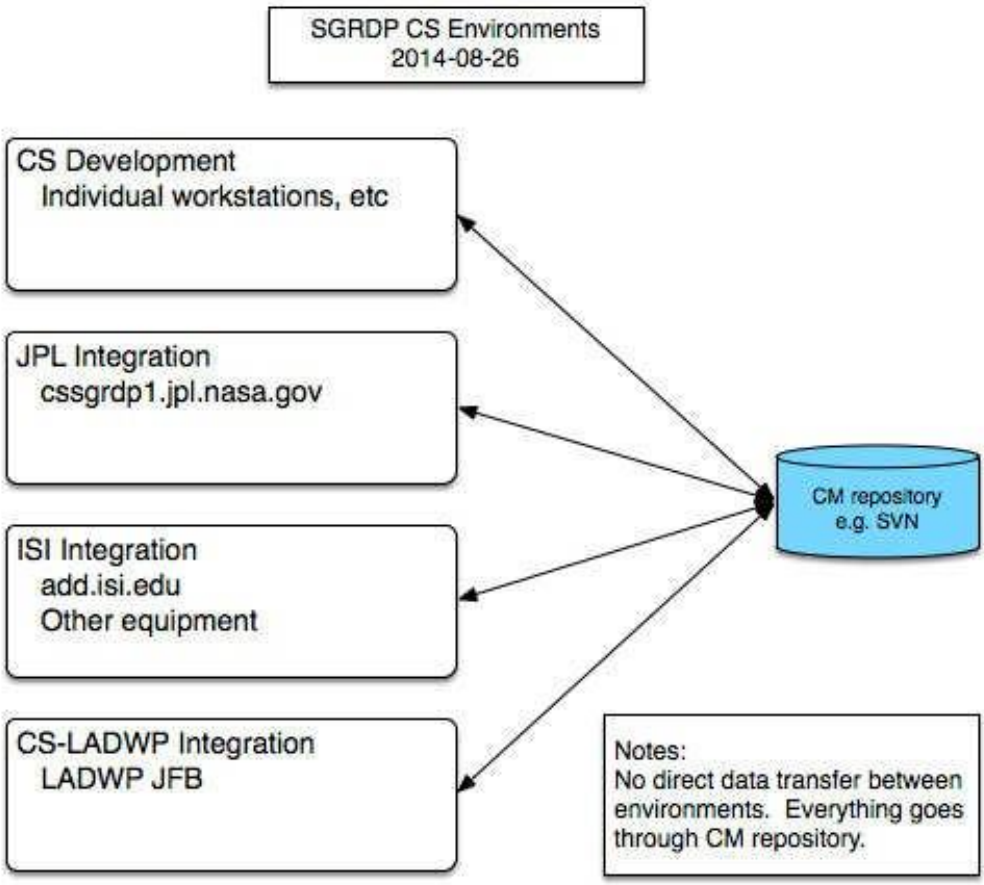


Figure 4-1: CS Integration Environments

Integration Environments

Initially CS developers are free to work in any suitable environment, using whatever tools necessary. Generally these will be individual developer workstations. There are no restrictions on the workstations, although we recognize that the more closely they resemble the operational environment, the fewer integration problems will arise.

Unit testing of each CS application is done at this level.

Source code is kept in a configuration Management (CM) repository. Software is developed on developers' systems and delivered to the CM system. It is then retrieved from the CM system for testing and deployment.

Machines used for the development and unit test activities Individual developer's laptops, desktop systems, and the JPL integration environment.

A CS team member, other than the developer of the particular component being tested, performs CS testing. The tester retrieves the component from the CM system into the CS testbed.

Dependencies among CS elements (*e.g.*, Visualizer on Detector) can be exercised here. The fidelity of this environment is close to the CS-LADWP Integration environment (see below), but the environments are not identical. This environment requires the flexibility to try things out and quickly address problems.

After successful testing, executable programs and build artifacts are put into CM along with the testing artifacts (procedures, scripts, input files, resulting outputs, logs, reports, etc).

Machines used for CS testing include:

cssgrdp1.jpl.nasa.gov (Red Hat Linux 6.4)

Copies of virtual machines (VMs) from LADWP location: csdev, ddrmom, csutil (using Oracle Red Hat Linux 6.2)

The components involved are:

Meter Data Test Sets, and Meter Data Simulator

DDR Database

Meter Data Anomaly Detectors

DDR Visualizer:

All components can be exercised on the single machine cssgrdp1. The key data flows are described below.

Meter data test sets are generated from exported actual meter data records, modified for various test scenarios, and are then stored as text files in the configuration management (CM) system.

The Meter Data Simulator (MDS) reads those files and inserts their records into the database to configurable destinations. MDS can pace the writing of data to the database at at a configurable rate (in a batch, or once per second, or every 5 seconds, etc.).

From this point on, the data flows are the same as for actual operational data. A Meter Data Anomaly Detector reads data from the database exactly as if it were from live operational meter data, without any knowledge that it originated from MDS. The detector writes anomalies found in that data to a different table within the database.

The DDR Visualizer monitors the several databases to obtain its inputs.

Verification Cases

CS-local Integration activities verify that all interfaces within the CS components operate as expected, and that there are no undesired interactions between components.

Interfaces			
ID	Interface	Test	Description
I3	DDR Database ☒ Meter Data Anomaly Detector (2- way)	Func	Producer transmits data of the expected format. Receiver accepts data of the expected format. Channel transmits data from the transmitter to the expected receiver with no modifications.
		Perf	Channel transmits data at the expected minimum and maximum rates. Channel transmits data within expected latency and error rates.
I4	DDR Database ☒ DDR	Func	Producer transmits data of the expected format. Receiver accepts data of the expected format. Channel transmits data from the transmitter to the expected

		Perf	Channel transmits data at the expected minimum and maximum rates. Channel transmits data within expected latency and error rates.

Verification Approach and Results

I3 (Func). MDAD implementation includes command-line options for more verbose outputs, including reporting the number and IDs of meters for which data was readable, some simple statistics on power readings (mean, standard deviation, etc.), and the number of detections per meter. Those outputs matched what was manually checked via the database interface, and in the case of Test Data Sets they matched the known quantities.

I3 (Perf) With ~3 months' of data, the Detector took ~4 hours to complete, so with 2 years' of data, a detection cycle (if not modified) will be ~32 hours. The bottleneck is not believed to be throughput.

I4 (Func) The DDR Visualizer displays a log of MDAD detections, which we verified by eye matched the on-screen MDAD output.

I4 (Perf) The DDR Visualizer explicitly provides feedback on the rate at which data arrives. We used command-line options in both the Meter Data Simulator and the MDAD to throttle flow to various rates, and verified by eye that, e.g., 1 output every two seconds, or 5 output every second, were shown correctly.

CS-LADWP INTEGRATION

Integration Environments

CS-LADWP integration testing is also done by a retrieving software and data from CM and installing it VMs within the LADWP SGRDP infrastructure. The executable software applications that are retrieved from CM are those that have already passed CS testing. The software is not rebuilt, as that might result in unintended changes being introduced into the executables.

The machines used include the following. All of these are VMs on an LADWP VLAN

csdev (op16vmsgDDR01.ladwpsmartgrid.com)

csutil (op16vmsgCSUTIL.ladwpsmartgrid.com)

ddrmom (op16vmsgDDRMOM.ladwpsmartgrid.com)

ddrami (op16vmsgDDRAMI.ladwpsmartgrid.com)

ddrdr (op16vmsgDDRDR.ladwpsmartgrid.com)

The components used include:

- AMI DCE Collector
- DDR Database
- Meter Data Anomaly Detector
- DDR Visualizer

Meter data flows are exercised from DCE to the AMI DCE Collector to the DDR Database on ddrmom, and the Detector and Visualizer are both run on csutil using the databases on ddrmom for input and output.

Additionally, all components are exercised on the single machine csdev.

Verification Cases

Integrating the CS components to LADWP systems involves verifying both that the CS systems run correctly when deployed on LADWP infrastructure, and that the CS interfaces to LADWP components function correctly.

CS/LADWP Integration Tests			
ID	**Test**	**Test**	**Description**
I1	DCE☒AMI DCE Collector	Func	Producer transmits data of the expected format. Receiver accepts data of the expected format. Channel transmits data from the transmitter to the expected
		Perf	Channel transmits data at the expected minimum and maximum rates. Channel transmits data within expected latency and error
I2	AMI DCE Collector ☒ Data	Func	Producer transmits data of the expected format. Receiver accepts data of the expected format. Channel transmits data from the transmitter to the expected

		Perf	Channel transmits data at the expected minimum and maximum rates. Channel transmits data within expected latency and error

D1	DWP Deployment	Func	All CS components can be installed on DWP infrastructure CS component dependencies are all present in DWP hosts CS components deployed on different hosts can communicate with each other.
		Perf	CS components have sufficient computing resources to execute on DWP hosts. CS components have sufficient storage available to meet performance requirements. DWP networking infrastructure provides sufficient bandwidth to meet CS-CS component communications needs
D2	DWP Integration	Func	AMI DCE has sufficient permissions and subscriptions to provide needed meter data to the AMI DCE Collector DCE Collector receives data as it is delivered by the DCE, and processes it for storage in the correct format in the CS Database.
		Perf	DCE Collector can receive AMI meter data and alerts for 50000 meters at the maximum expected burst rate with less than 1% data loss. DDR Database is capable of storing data for 50,000 meters at maximum expected burst rates. Detectors are capable of receiving and executing detection

Verification Approach and Results

Here is how each above verifications was performed:

I1 (Func) The AMI DCE Collector was able to receive and process data of the expected format from the DCE with no errors.

I1 (Perf) VM statistics for free RAM and CPU usage showed greater than 90% margin.

I2 (Func) We observed ~47,000 individual meter IDs in the database with ~11,000,000 events. We expect ~50,000 meters to be reporting.

I2 (Perf) VM statistics for free RAM and CPU usage showed greater than 90% margin.

D1 (Func) The MDAD was run on the production VMs at DWP, specifically on csutil using the databases on ddrmom.

D1 (Perf) VM statistics for free RAM and CPU usage showed greater than 90% margin. Disk space growth has not been linear enough to forecast.

D2 (Func) DCE data flow has been configured in all network resources to ensure that data flows from the DCE to CS components.

D2 (Perf) VM statistics for free RAM and CPU usage show greater than 90% margin. Disk space growth has not been linear enough to forecast.

END-TO-END SCENARIO

The following segments describe scenarios that exercise the detection pipeline. These have already been demonstrated to LADWP, and are included here for completeness.

Meter Data Anomaly Detection

This sample scenario describes activities that might occur that result in the identification and display of a *meter data anomaly (MDA)* event, such as possible energy theft, AMI by DDR.

The key source of data for this scenario is the AMI Data Collection Engine (DCE). The DCE provides the back-office interface to the Itron Advanced Metering Infrastructure (AMI). DCE specifically provides meter-related data via a web services interface. Client programs subscribe to data if interest, which are then pushed to clients as they are received by DCE.

The DDR AMI DCE interface software subscribes to meter usage data for meters. As it receives data from a meter M, the client writes the data to the DDR database. A DDR MDA detector obtains current and historical usage data for M from the database. Using its detection algorithm, it compares current and historical usage for M to identify potential MDAs for M. When it detects a possible MDA, it generates an event describing what it has detected and writes the event to the DDR database. The DDR Visualizer obtains events, including MDA events, from the DDR database.

End-To-End Verification

The end-to-end scenario was run in two configurations for verification of integration:

With simulated meter data, using the same data sets as the unit test.

With production data, to ensure that the flow and contents of operational data are correctly handled.

In both cases, the entire pipeline was verified to behave as expected, exercising all interfaces as listed individually above. Using the simulated meter data, detector performance was comparable to the unit test results, suggesting that the detectors behave as designed in integration.

Appendix Q SGRDP Report on Integration of Basic Detectors

LADWP Smart Grid Regional Demonstration Program

Cyber Security (CS) Document

DDR August 2014

SGRDP Report on Integration of Basic Detectors within the DDR Cyber Security Components

Version 1.2

August 31, 2014

Date	Version #	Reason for Change(s)	Author(s)
8/31/2014	1.2	Final Version (pdf merged with Appendix)	Gaurav Mittal, Capgemini
8/31/2014	1.1	Final Version (.doc)	Clifford Neuman, USC-ISI
8/15/2014	1.0	Initial draft outline	Clifford Neuman, USC-ISI
			(JPL, DWP, and Gaurav, as authors also on the combined submission when the individual parts are assembled)

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AN OVERVIEW OF THE DEMONSTRATION

Smart grid capabilities and functions demonstrated

This report is focused on the ability to detect anomalous and routine network and host events on routers and hosts running smart grid demonstration components, and record such events in the Computer Security Database. A companion report focuses on ability to detect anomalous patterns of consumption data from meters.

Smart grid impacts and benefits demonstrated

Capability to detect anomalous and routine network and host events on routers and hosts.

List of objectives/Scope

To collect reports of anomalous and routine network and host events and to record those reports in the CS Database which is used for diagnosis tools and to initiate remediation activities within the SGRDP.

Mapping to the SOPO & Deliverables

The deployment of the basic detectors supports CS Demonstration

“demonstration of the grids active and redundancy defenses against cyber-attack. It will demonstrate the accuracy and timeliness of detection…” and CS Demonstration

“the ability of the SmartGrid to detect … compromises of system integrity including software and firmware modifications and the addition of unauthorized physical components to the system.

Note that this report is focused on detectors, and hence the demonstration descriptions above were paraphrased to include only the detection components. Remediation and Response capabilities will be described in other reports, as those capabilities mature based on observed data.

OVERVIEW OF THE SYSTEMS UTILIZED IN THE DEMONSTRATION (IF APPLICABLE)

Interactions with subsystems/components

Data collection occurs on the following SGRDP components, and data is transmitted to the server DDRMOM (and in one instance to CSDEV) where the data is placed into the CS Database (implemented using Mongo DB).:

The CS Firewall, a blade that routes certain data between the external internet and domains within the SGRDP, as well as between domains in the SGRDP (except for those transitions which are managed through the DataPower Appliance).

Monitors running on each of the virtual machines running in support of the computer security capabilities of the SGRDP.

Once deployed on the machines supporting EV, DR, and CB, monitors running on those machines. The monitors on the CS computer demonstrate the capability, but still pending system integration activities have prevented the deployment of these monitors on machines by the other projects to date.

That AMI data collection engine send data to the AMI Collector (the AMI DCE collector process subscribes to the collection engine). The data from the collection engine is processed by the collector and submitted to the CS Database (presently the instance running on CSDEV).

The CGNMS, part of the AMI communications infrastructure, communicates event data to the CGNMS collector, a CS component subscribed to CGNMS event streams. The CGNMS collector, a CS components currently running on the same virtual machine as the AMI collector), processes that data and submits records to the CS Database.

SIEM – Selected event records received by the CS Database are sent via the syslog interface to the SIEM for further visualization and fusion with other data.

Technologies and systems used in the demonstration

Mongo Database – Database was deployed on CSMOM and CSDEV machines and accepts records from the components labeled a-e above. Additionally, the software running on CSDEV which writes event records into the CS Datbase generates syslog entries for a subset of the events, with those syslog entries forwarded to the SIEM for additional visualization within the SIEM.

CS Firewall – A system running a linux based firewall router that connects outside communications to the SGRDP zones, and which supports transit across zones within the SGRDP (except for those transitions using the application Proxy Data Power Devices). This firewall has been modified to collect additional event data based on pattern matches and based on network flow statistics. The CS Firewall also monitors its own heath (with the same capabilities as provided for other machines within the SGRDP) and reports back to the CS Database with data regarding data bandwidth, traffic patterns matching configured filters, and host health statistics.

The Snare program has been obtained and provided to other components of the SGRDP (in particular, to DR) where it reads windows log files and acts as a monitor to submit data to the CS Database. The communication from Snare is accepted, processed, and then placed in the CS Database for use in subsequent diagnostics.

Specialized monitors running on the computer security hosts collect additional data about the processes running on the system, and includes capabilities to make changes (terminate, nice, etc.) those processes. It is our intent that these monitors run on all SGRDP servers, but that requires completion of additional system integration activities.

The process that accepts data on CSMOM for insertion to the CS Database also filters the incoming information and additionally submits selected information to the SIEM for visualization and analysis.

Descriptions of the methodologies and algorithms utilized

a) The Basic DDR delivery demonstrates that capabilities of the collection framework to collect data, perform very basic analysis of the data to detect relevant and actionable events, and to show how

remediation activities are communicated to the policy enforcement points throughout the system. An advanced DDR capability is under development (per the original plan, this capability is constructed based on the data that is now being collected within the SGRDP). The methods for collecting the data have been described in section 3, above, for each of the CS components participating in the data collection.

Summaries of the results of the performance of the smart grid systems and technologies derived from lab tests, field tests, or grid-connected applications.

a) A demonstration of the basic DDR components of the SGRDP was performed in June of 2014. Performance of the DDR components was sufficient for the demonstration, but we were not seeing live data at that time. Since the system has become operational we have not observed any performance issues. We have observed issues with the loss of subscriptions to the AMI and CGNMS collectors, and have addressed these issues through the addition of a server process that monitors for loss of data and submits a re-subscription request in response.

Summaries of the results of the analysis and benefits.

a) The data collected has been sufficient to demonstrate the basic DDR activity within the SGRDP. We have had limited success in coordination with the other teams to obtain data from their hardware components, despite having provided them with software to collect the data from their servers. An earlier system integration effort would have greatly assisted us in this regard.

Summary of the major findings and conclusions including lessons learned and best practices.

a) The system is operational but we only have access to data from the operational system over a short timeframe. Additionally, the visibility of the SGRDP components to potential adversaries has been limited until recently, and we have not yet observed attacks directed to the infrastructure. As development of advanced DDR capability continues we anticipate that there will be additional sources of data needed for differential diagnoses, etc. These will constitute lessons learned, and will result to updates for the basic collection components.

Summary of future plans and next steps with respect to additional testing, demonstration, or deployment

a) Per the original plan, continued work on the DDR activity will encompass development of advanced detectors, diagnosis, and remediation components that deprive situational awareness of the system as a whole based on the data that has been collected using the infrastructure described herein. As we see attacks and failures in practice, we anticipate that there may be additional information not currently in our data sets that are needed to support differential diagnoses, etc. As such additional data is identified, the detection component will be extended if necessary to obtain the additional inputs.

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A. DDR Delivery Description (March 2014)

B. CS DDR March Delivery Demonstration Host and Network Infrastructure DDR

LADWP Smart Grid

Regional Demonstration

Cyber Security (CS) Document

DDR March 2014

Delivery Description

Version 1.4

Date	Version #	Reason for Change(s)	Author(s)
2/28/2014	1.0	Imported materials from previous overview document, and added notes from 2/28/2014 meeting	JPL CS team
3/26/2014	1.1	Updated to reflect recent changes.	JPL CS team
3/28/2014	1.2	Updated to include more contextual info.	JPL CS team
6/3/2014	1.3	Updated with more detailed scenarios	BCN
6/5/2014	1.4	Reviewed, updated formatting, removed fig. 3	Gaurav M

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1. Introduction

1.1 Objectives

The purpose of this document is to describe informally the part of the DDR March 31, 2014 delivery that be used for demonstration.

1.2 Summary

The March 31, 2014 DDR delivery demonstrates a simple, operationally relevant scenario for DDR execution. This shows that both a basic DDR design and a deployment infrastructure are in place, upon with more sophisticated detection, diagnosis, and remediation capabilities can be built. The delivery demonstrates representative flows of data through the system.

The delivered software executes within the SGRDP computing infrastructure at LADWP. Figure 1 is the component diagram representing the SGRDP, which provides the context in which DDR functions. The CS components are shown in blue. The lines of communication between the components are also shown.

The DDR March 31, 2014 delivery has the capability to:

Basic Cyber DDR:

- Obtain records of detected network events incident to the CS Firewall.
- Store those records in an operational DDR database.
- Obtain CPU, network, and other system status from CS monitored components, including firewall machines.
- Store the status information in an operational DDR database.
- Perform detection of network and host anomaly events.
- Implement simple remediation actions to block certain events or to mitigate the impact of such anomalies, in response to detected network and host anomaly events.
- Provide a simple way to visualize the processing and data flow for the sample scenario, and display detected events.

Basic Cyber-Physical DDR

- Connect to the operational AMI Data Collection Engine (DCE) running at LADWP to obtain meter usage data from AMI meters.
- Store that operational meter data in DDR database.

- Generate simulated meter data and store that simulated meter data in the DDR database.
- Perform detection of real and/or simulated “meter data anomaly” events from the real and/or simulated meter data.
- Provide simple visualization the processing and data flow for the sample scenario, and display detected events.

The top-level data flow for demonstration scenario is shown in Figure 2.

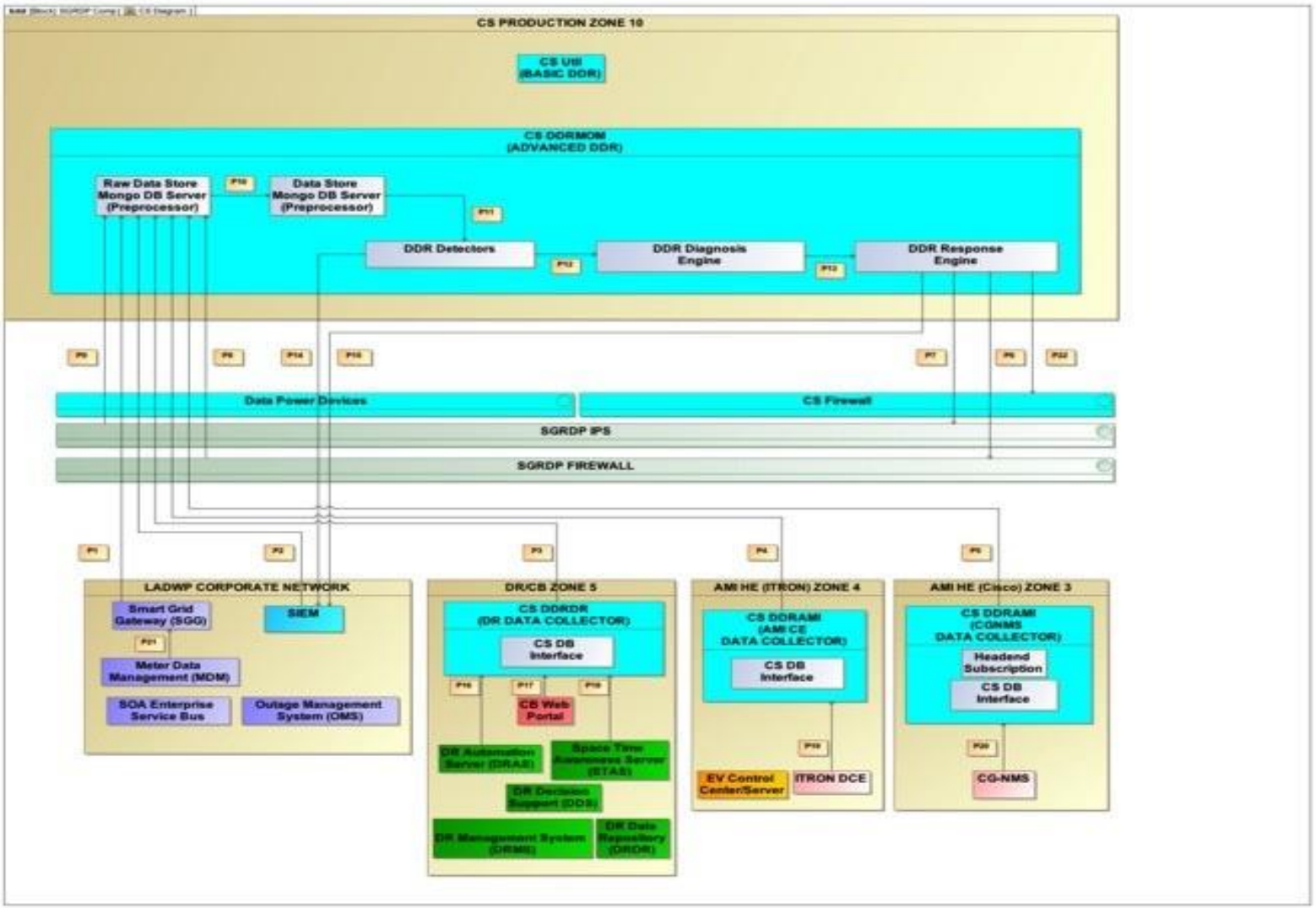


Figure 1: SGRDP Context for DDR

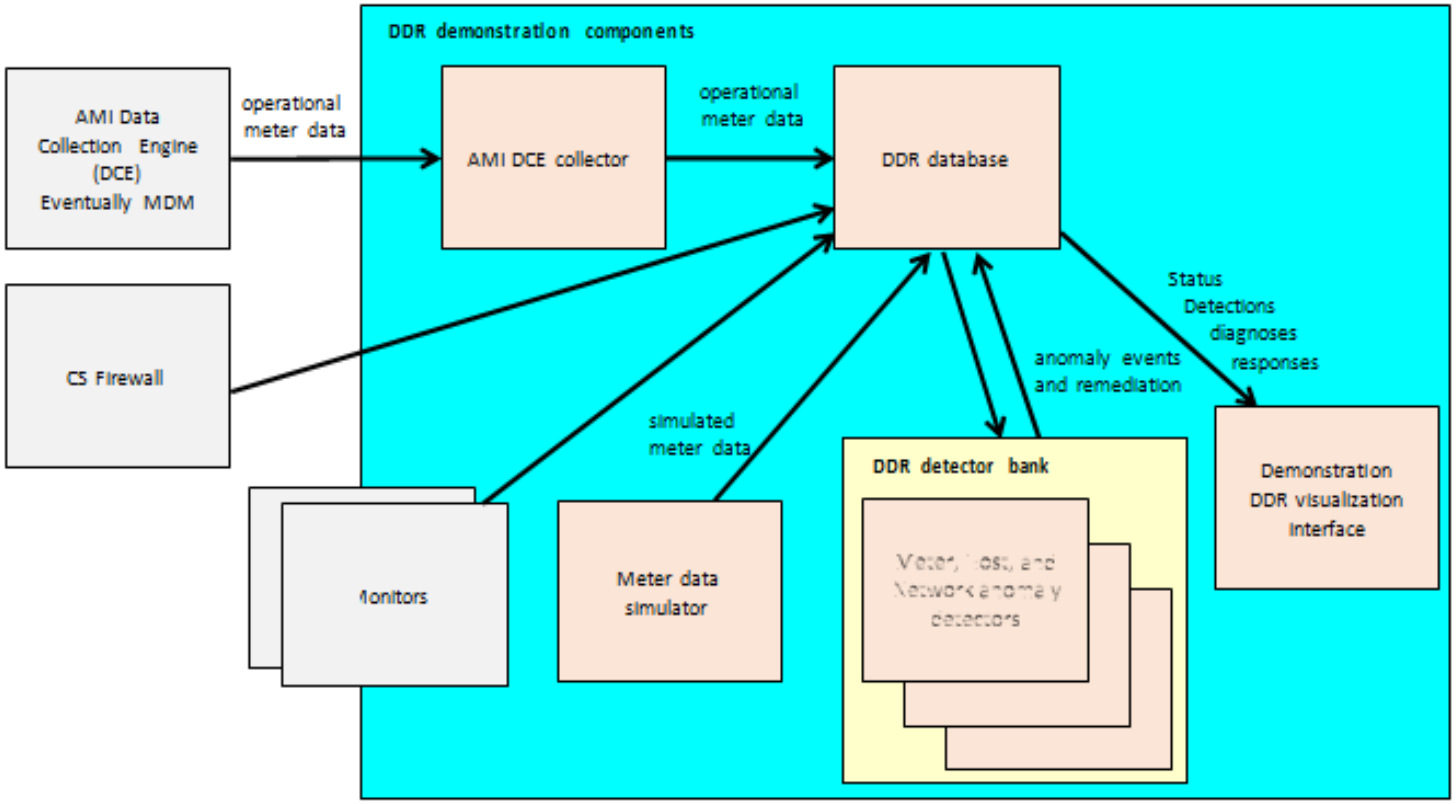


Figure 2: DDR Data Flow for Demonstration

2. Sample Cyber-Physical Scenario Energy Theft

Energy theft is identified as a key scenario in the CS demo matrix (labeled *DDR-Energy-Theft- AMI*). The March 31 delivery focuses on a subset of the functionality required to support the identification of energy theft that is accomplished by cyber-attack.

Energy theft test scenarios have been constructed with a baseline data set to inject each of the above conditions at a fixed time in the dataset:

- Baseline: Average daily profile with no energy theft injected.
- Scale factor: Usage measurements scaled to a percentage of actual usage.
- Constant bias: Usage measurements shifted by a constant value.
- Clipped profile: Usage measurements capped at a maximum value.
- Flat profile: All measurements set to a constant value.

Test data sets containing one month of usage data, including an injected energy theft, were generated from analysis of production usage data, and then modified for use in test. Fixed files were then produced that will be read into the meter data simulator, and played back into the database, per the flow in Figure 2. For each case, there is one injected anomaly (the sudden change from baseline behavior to theft-like behavior). Detector performance is measured by whether it is able to detect the injected shift in behavior, and by the number of false alarms it raises.

Testing of the infrastructure (data flow, record generation, etc.) benefits from more than one detection event per test, so there will also be test cases where the detector is tuned to generate a large number of events that would be considered false alarms.

2.1 Energy Theft Scenario

The goal of a malicious customer in stealing energy is to have the system report fewer watt- hours than the customer uses. As computing devices, smart meters provide new software- based paths to accomplish that goal. They also allow finer insight into the state and performance of metering, which can be used to detect a condition that may signal ongoing energy theft. By monitoring meter consumption data alone, it is possible to identify changes in the behavior of consumption measurements that may be symptomatic of energy theft. Energy theft scenarios that involve a compromise of the meter to modify the software behavior are considered the primary cases within this scenario that are in scope for the CS effort. The following behaviors in usage measurements are derived from an analysis of attack vectors through the meter itself.

A particular concern in detecting energy theft is that the apparent symptoms of it may actually be result of benign changes or variations in customer behavior. Because of this, detection of sudden changes in meter behavior are marked as *meter data anomalies* (not energy theft) that can then be investigated by the utility, or sent to (yet to be implemented) diagnosis routines that will correlate meter data events with other system events to increase confidence that a particular event is relevant.

2.2 Meter Data Anomaly Detection

This sample scenario describes activities that might occur that result in the identification and display of a *meter data anomaly (MDA)* event, such as possible energy theft as described above, by DDR.

The key source of data for this scenario is the AMI Data Collection Engine (DCE). The DCE provides the back-office interface to the Itron Advanced Metering Infrastructure (AMI). DCE specifically provides meter-related data via a web services interface. Client programs subscribe to data if interest, which are then pushed to clients as they are received by DCE.

The DDR AMI DCE interface software subscribes to meter usage data for meters. As it receives data from a meter M, the client writes the data to the DDR database. A DDR MDA detector obtains current and historical usage data for M from the database. Using its detection algorithm, it compares current and historical usage for M to identify potential MDAs for M. When it detects a possible MDA, it generates an event describing what it has detected and writes the event to the DDR database. The DDR GUI obtains events, including MDA events, from the DDR.

3. Sample Network Host (Cyber) Scenarios

Responding to cyber-attacks is a key scenario in the CS demo matrix. Cyber-threats include denial of service attacks on smart grid infrastructure, to prevent demand response and other commands from being implemented as needed to maintain operational resiliency of the power grid, as well as targeted penetration attempts on public facing smart grid components, and through multiple stage attacks on internal components. Diagnosis and remediation of such attacks requires collection of information on the baseline operation of the system, which will be collected once the system is operational. The basic DDR components delivered in the March release provides the basic framework into which advanced detectors, and diagnosis and remediation capability will be deployed. Three basic cyber-threat DDR capabilities are included to demonstrate the operation of the framework, and are to be demonstrated.

3.1 Detected Attack Packet Scenario

This scenario describes activities that occur as the result of the monitoring of packets at the CS firewall that match pre-specified attack signatures. It demonstrates capabilities that will apply also in later advanced DDR scenarios to signatures and anomalous activity detected over multiple sources of network monitoring, including the CS firewall, and host-associated firewalls across the protected hosts in the SGRDP.

The key source of data for the basic scenarios is the monitoring component of the CS firewall, with records of traffic matching pre-specified filters communicated to the DDR database. Of the traffic matching pre-specified filters, some subset of the filters will trigger an autonomic response on the firewall itself, in addition to sending data to the DDR database.

The DDR Cyber Detector component (initially deployed on the same machine as the CS database, but eventually running on a separate VM within the CS zone), subscribes to events from the CS database generated by the Network and Host monitors. Upon detection of attack signatures, the remediation engine generates remediation rules to block traffic from specified addresses, and those rules are inserted into the CS database. The deployed firewall components (for now the CS firewall, but eventually any host based firewalls as well) subscribe to the updates placed into the CS database by the remediation engine, and implement the change to their policies, blocking further packets from the detected source of the attack.

A visualization tool will enable the demonstration of the receipt of packets matching pre- specified signatures, as well as the change to policies which are implemented and enforced at the firewall. Demonstration of this scenario will be based on the generation of packets outside of the DWP network, destined for SGRDP hosts, with signatures matching pre-specified rules which will trigger the remediation activity.

3.2 Internal DoS - Rate Limitation Scenario

This sample scenario describes activities that occur as the result of the monitoring the data rate between pairs of communicating entities within the SGRDP. The scenario will be demonstrated on flows into the CS database from the components collecting AMI, firewall, and host monitoring data. The rates of data transmission across the CS Firewall boundary will be monitored to generate baseline minimum flow rates, and the system will be configured to enforce a maximum flow rate. Deviations from this interval will be flagged and communicated to the CS database.

The DDR Cyber Detector component (initially deployed on the same machine as the CS database, but eventually running on a separate VM within the CS zone), subscribes to events from the CS database. Events indicative of flows less than the established minimum expected rate will trigger detection of host

or network problems, and an alert will be generated and stored in the CS database, with such alerts subscribed to by visualization and network monitors. A

record indicating that the maximum flow has been exceeded will result in a similar alert stored in the CS database, as well as the generation of remediation actions, also stored in the CS database. The remediation records are subscribed to by the firewall, which can enforce the remediation action, which may require changes to enforced rate limitation on the flows between the particular pair of entities. Prior to the change in rules, the firewall will astronomically impose rate limitation based on a pre-configured limit on the flow rate.

Demonstration of this scenario will occur by creating additional sources of (dummy) events to be placed in the CS database, such that the source of dummy events will exceed established limits. The firewall will clamp down on those flows sufficiently to allow the CS database to continue processing flows from the other (non-compromised) sources. This capability improves the resilience of DDR to denial of service that would otherwise occur if any of the monitors (present on machines outside the CS zone) were to be compromised. The capability is more generally useful to prevent denial of service attacks on other components within the SGRDP, including CB and DR resources.

3.3 Compromised/Runaway Process Scenario

This scenario describes activities that occur as the result of the monitoring of system resources and processes on monitored and protected machines. In the demonstration, the monitored and protected machines are the CS database, the CS Firewall, and possibly the AMI and DR collector machines.

Monitors on protected machines generate event records with information about process creation, resource utilization, and system load, which are sent to the CS database. The DDR Cyber Detector component (initially deployed on the same machine as the CS database, but eventually running on a separate VM within the CS zone), subscribes to events from the CS database. Events indicative of contention for system resources trigger an assessment of the consumption of individual processes. If an individual process is determined to be consuming significantly greater resources than is normal (an anomaly condition), a remediation record is generated alerting operators to the problem. The monitors on the protected machine subscribe to remediation records regarding their own activities, and the generated record will result in remediation action initially re-nicing the offending processes, but in advanced DDR, this action may result in restarting or terminating processes as well.

4. Key DDR Components

4.1 AMI Data Collection Engine (DCE) Interface Software

The AMI DCE interface software subscribes to the DCE for meter-related data of interest, receives the data from DCE, and writes the data to the DDR database.

4.2 Meter Data Simulator

The meter data simulator generates simulated meter data. This functionality is required during subsystem testing. The simulator is used to create data containing simulated anomalies, statistically significant larger data sets, a fault-injected test corpus, etc.

The output format for the simulated data is the same as the format of the data generated by the AMI DCE interface software, except that there is indicator flag in each record indicating whether the source is the AMI DCE interface software or the meter data simulator.

4.3 DDR Database

The DDR database is the central repository for data received by DDR, as well as other data generated by DDR internally (e.g., detected events).

4.4 Meter Data Anomaly (MDA) Detector Bank

The MDA detector bank is designed to contain a diverse set of detectors. The detector bank obtains data (*e.g.*, meter usage data from the DDR database) after which each detector, or combination of detectors, will analyze the data to detect potential MDA events. The infrastructure is designed to be flexible, in that it allows the incorporation of new detection algorithms that may be better suited to new and evolving threat scenarios. The detector bank writes detected events back to the DDR database.

4.5 Network and Host Anomaly (NHA) Detector Bank

The network and host detector banks are designed to contain a diverse set of detectors. The detector bank obtains data (*e.g.*, network rates, packet summaries, log data, host statistics from the DDR database) after which each detector, or combination of detectors, will analyze the data to detect potential network and host anomaly events. The infrastructure is designed to be

flexible, in that it allows the incorporation of new detection algorithms that may be better suited to new and evolving threat scenarios. The detector bank writes detected events back to the DDR database. At present, the detector is also capable of writing simple scripted remediation commands to the DDR database, though this functionality will be moved to a separate remediation component in advanced DDR.

4.6 DDR Visualization Interface

The DDR visualization interface obtains events of interest from the DDR database and displays them to the user. While a basic visualization interface is provided within the DDR itself, it is expected that visualization will utilize more flexible visualization tools from the SIEM.

Cyber Security (CS) Document

August 2014

Appendix B

Version 1.0

August 31, 2014

CS DDR March Delivery Demonstration
Host and Network Infrastructure DDR

June 12, 2014

Agenda

- CS Demonstration Items
- CS Design Background
  - Containment architecture
    - Including the CS firewall
  - DDR emulation architecture
  - DDR Architecture
- Host and Network DDR Threat Scenarios
  - Scope and Goals
- Demo

CS Software Components Demonstrated

- The host/network DDR demonstration relies upon:
  - The jointly designed containment architecture implemented through DWP firewalls and vlan containment.
  - The CS firewall used for monitoring and remediation, implemented at ISI.
  - CS database / information flow architecture, jointly designed and used for all aspects of DDR (infrastructure and cyber-physical), and implemented at ISI using “the Mongo Database”.
  - ISI developed collectors (AMI and CGNMS), and some of the monitors for firewall and endpoint protection.
  - An initial front-end/GUI for infrastructural DDR.

Overview of Demonstration

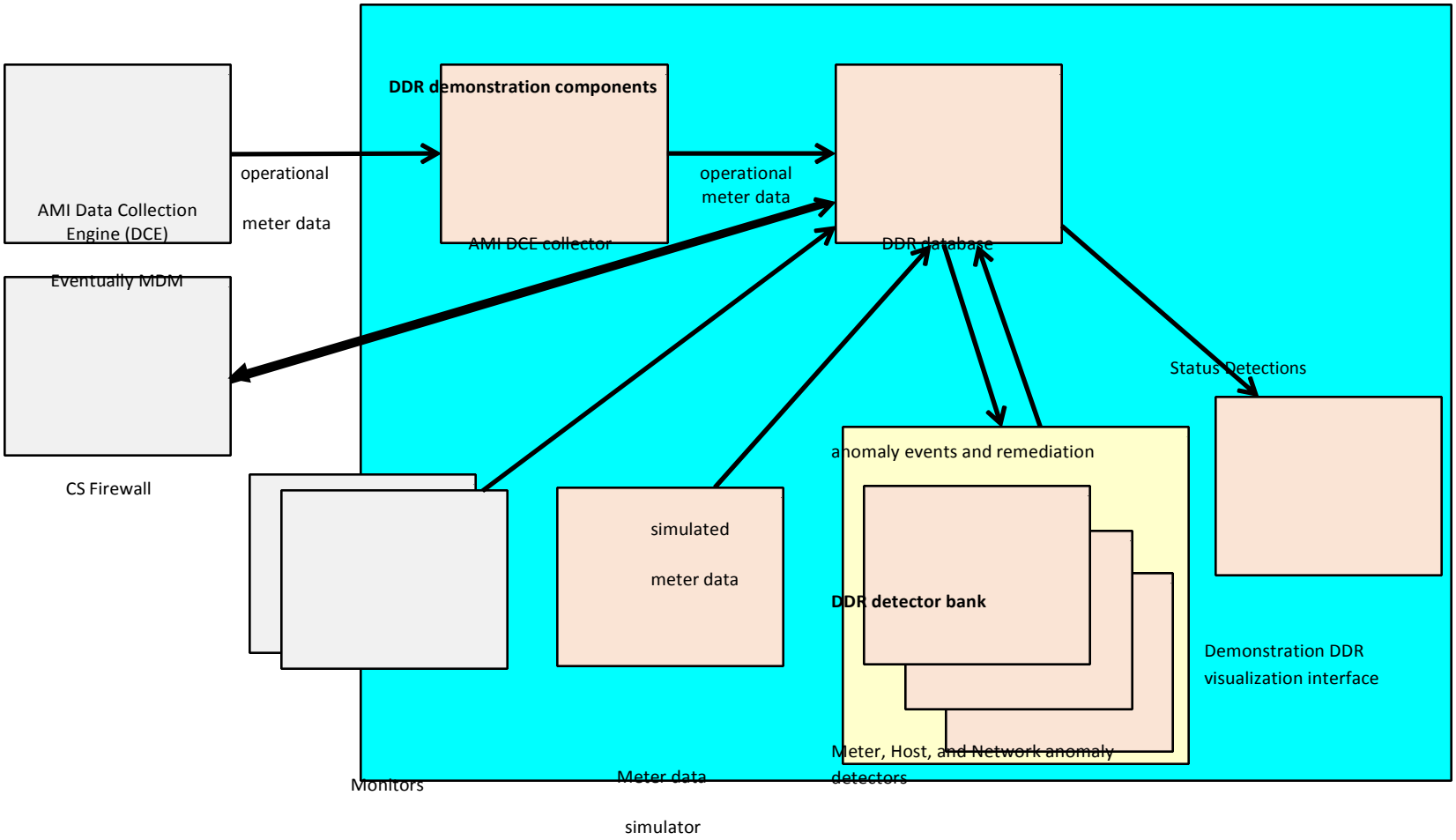
- The demo shows the cornerstone of CS protection: establishing a communications protection boundary and detecting/reacting to traffic across that boundary.

- The CS system is always running, and consists of the following components implemented at ISI:

- 1. data collectors
- 2. database
- 3. Infrastructure (host/network) DDR
- 4. The CS firewalls

- Other components developed at ISI to validate the above:
  - AMI emulation environment which allowed work to proceed before AMI deployment occurred.
  - Emulated DR modules using same LBNL software core as UCLA with DDR and STAS interfaces.
  - CGNMS emulator
  - AMI headend emulator
  - meter group emulator
  - STAS emulator
  - SQL-compatible database for the above
  - console extensions to manage the above graphically
- Developed and validated in a test bed at ISI with identical OS, software environment, and IP addresses, to replicate DWP environment

DDR Architecture



Detector Bank

The detector bank is basic element that houses several implemented detectors.

Power-theft and CP anomaly, by JPL

Network attack detection, by ISI

Arbitrary number of detectors on any data

available in the database.

All detection events will be written to the database for later follow-up.

Diagnosis and remediation events also written to the database.

Infrastructure DDR Demonstration Goals

Demonstrate a subset of capabilities required to address the infrastructure attacks.

Collect and process live data

Detect attacks and demonstrate simple remediation

Show monitoring of infrastructure status

Overview of Demonstration

This demo will show:

Service protection

detect traffic to/from sensitive ports/addresses react by blocking (timer/explicit reset)

Bandwidth protection

detect traffic in excess of a threshold

react by blocking (timer reset or explicit reset) react by pacing (timer/explicit reset)

Process protection

detect runaway processes on monitored infrastructure react by nicing the affected processed

This CS demonstrates first-order cybersecurity protection that focuses directly on communication resources.

Detected Attack Packet Scenario

Focuses on monitoring of packets at the CS firewall that match pre-specified attacksignatures.

monitoring component of the CS firewall recordstraffic

matching pre-specified filters to the DDR database

Some events trigger autonomic response (not shown)

Detector (from detector bank) further analyzes recordsin DDR database and to diagnose an attackcondition.

Remediation rules are generated to block traffic from specified addresses, and those rules are inserted into the CS database.

The deployed firewall components (for now the CS firewall, but eventually any host based firewalls as well) subscribe to the remediation prescriptions and implement the change to their policies, blockingfurther packets from the detected source of theattack.

Rate Threshold Scenario

Focuses on monitoring the data rate between pairs of communicating entities within the SGRDP.

In the live system, rates of data transmission across the CS Firewall boundary will be monitored to generate baseline minimum flow rates. In the demonstration, the baseline rates are set manually to faclitate the demo.

System is configured to enforce a maximum flow rate. Deviations from this interval will be flagged and communicated to the CS database.

The DDR Cyber Detector component subscribes to events from the CS

database.

Events indicative of flows less than the established minimum expected rate will trigger detection of host or network problems, and an alert will be generated and stored in the CS database

A record indicating that the maximum flow has been exceeded will

result in a similar alert stored in the CS database.

A remediation action will be generated and placed into the CS database to block the flow, or to bandwidth limit the flow to a specified rate.

The CS firewall will read the remediation action from the database and

apply the prescribed action.

Focuses on monitoring the processes running onmonitored hosts. Anomalous changes to resources consumed result in remediation.

Process state changes are monitored on hosts within theSGRDP.

Consumption above pre-specified thresholds result inevent records sent to the CS database.

Detectors reading records from the CS database can identify patterns of records indicative of coordinated attacks or software problems, and take appropriate remediation actions across the entire SGRDP, including adjusting the priority, restarting, or terminating process.

In this demonstration, we show autonomic response, based on pre-specified remediation responses that occur on the monitored node directly, in this case adjusting the priority ofthe process.

LADWP Smart Grid Regional Demonstration Program

Cyber Security (CS) Document

DDR August 2014

Integration of SGRDP Detection & Diagnosis – Basic

Version 1.2

Date	Version #	Reason for Change(s)	Author(s)
8/31/2014	1.2	Version (merged with Appendices)	Gaurav Mittal, Capgemini
8/31/2014	1.1	Final Version (.doc)	Clifford Neuman, USC-ISI
8/15/2014	1.0	Initial draft outline	Clifford Neuman, USC-ISI
			(JPL, DWP, and Gaurav, as authors also on the combined submission when the individual parts are assembled)

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AN OVERVIEW OF THE DEMONSTRATION

Smart grid capabilities and functions demonstrated

Ability to diagnose problems within the smart grid demonstration, especially with respect to attacks on system components, and to initiate remediation to mitigate the impact of such attacks and failures.

Smart grid impacts and benefits demonstrated

Capability to diagnose attacks and failures on network and host components and take action based on those findings.

List of objectives/Scope

To diagnose faults and attacks based on reports collect by the detection components of anomalous and routine network and host events as recorded in the CS Database and to initiate remediation activities within the SGRDP.

Mapping to the SOPO & Deliverables

The deployment of the basic detectors supports CS Demonstration 1, "demonstration of the grids active and redundancy defenses against cyber-attack. It will demonstrate the accuracy and timeliness of detection and response" and CS Demonstration 2, "the ability of the SmartGrid to detect and recover from compromises of system integrity including software and firmware modifications and the addition of unauthorized physical components to the system.

OVERVIEW OF THE SYSTEMS UTILIZED IN THE DEMONSTRATION (IF APPLICABLE)

Interactions with subsystems/components

Data collection, diagnosis, or remediation occurs on the following SGRDP components. While this report is focused on diagnosis and remediation, this capability depends on detection capabilities described in an earlier report and repeated here for completeness. The descriptions of the components below are labeled with respect to the function (detection, diagnosis, or remediation) facilitated:

1. The CS Firewall (detection, autonomic diagnosis, and remediation), a blade that routes certain data between the external internet and domains within the SGRDP, as well as between domains in the SGRDP (except for those transitions which are managed through the DataPower Appliance).
2. Monitors (detection and remediation) running on each of the virtual machines running in support of the computer security capabilities of the SGRDP.
3. Once deployed on the machines supporting EV, DR, and CB, monitors running on those machines. The monitors on the CS computer demonstrate the capability, but still pending system integration activities have prevented the deployment of these monitors on machines by the other projects to date.
4. That AMI data collection engine (detection) send data to the AMI Collector (the AMI DCE collector process subscribes to the collection engine). The data from the collection engine is

processed by the collector and submitted to the CS Database (presently the instance running on CSDEV).

5. The CGNMS (detection), part of the AMI communications infrastructure, communicates event data to the CGNMS collector, a CS component subscribed to CGNMS event streams. The CGNMS collector, a CS components currently running on the same virtual machine as the AMI collector), processes that data and submits records to the CS Database.
6. SIEM – (visualization) Selected event records received by the CS Database are sent via the syslog interface to the SIEM for further visualization and fusion with other data.

Technologies and systems used in the demonstration

1. Mongo Database – (detection, diagnosis, and remediation) Database was deployed on CSMOM and CSDEV machines and accepts records from the components labeled a-e above. Additionally, the software running on CSDEV which writes event records into the CS Database generates syslog entries for a subset of the events, with those syslog entries forwarded to the SIEM for additional visualization within the SIEM. The database also receives records from the diagnosis instances when a diagnosis component makes a diagnosis, and if the component generates remediation instructions, those instructions are also written to the database.
2. CS Firewall – (detection, autonomic diagnosis, and remediation) A system running a linux based firewall router that connects outside communications to the SGRDP zones, and which supports transit across zones within the SGRDP (except for those transitions using the application Proxy Data Power Devices). This firewall has been modified to collect additional event data based on pattern matches and based on network flow statistics. The CS Firewall also monitors its own heath (with the same capabilities as provided for other machines within the SGRDP) and reports back to the CS Database with data regarding data bandwidth, traffic patterns matching configured filters, and host health statistics. The CS firewall is capable of making diagnosis based on locally collected data (autonomic diagnosis). Such diagnoses are based on rules loaded to the firewall in advance. The CS firewall can take atomic remediation actions based on such diagnoses. In the normal case, the CS firewall also monitors relevant data added to the CS database by the separately located diagnosis engine and takes remediative action based on those rules.
3. The Snare program (detection) has been obtained and provided to other components of the SGRDP (in particular, to DR) where it reads windows log files and acts as a monitor to submit data to the CS Database. The communication from Snare is accepted, processed, and then placed in the CS Database for use in subsequent diagnostics.
4. Specialized (detection and remediation) monitors running on the computer security hosts collect additional data about the processes running on the system, and includes capabilities to make changes (terminate, nice, etc) to those processes in response to remediation instructions placed into the CS database by the diagnosis and remediation engine. It is our intent that these monitors run on all SGRDP servers, but that requires completion of additional system integration activities.
5. The process that accepts data on CSMOM for insertion to the CS Database (visualization) also filters the incoming information and additionally submits selected information to the SIEM for visualization and analysis.
6. Diagnosis and Remediation bank – Multiple diagnosis monitors run (presently on CSMOM, the home of the CS Database) to monitor data as it enters the CS database in order to generate a situational awareness of the SGRDP and to detect patterns of events that are indicative of an

attack or failure. Upon forming a preliminary diagnosis of a failure or threat condition, additional data may be checked to further refine the diagnosis (differential diagnosis). When a diagnosis is confirmed, the diagnosis component writes a new record into the CS database identifying the condition. Some of the diagnosis components are also capable of generating remediation instructions, targeted to specific policy enforcement points which will implement the remediating activity.

7. Per the original plan, development of advanced capability for diagnosis and remediation is ongoing, as we develop the components based on data being currently observed in the operating phase of the SGRDP. A simple diagnosis and remediation components was developed for and demonstrated in the Basic DDR demonstration in June. That component monitors the CS Database for records from the CS firewall matching 1) a particular attack signature, and 2) excessive communication between pairs of components indicative of a denial of service attack. Upon detection, these components record the diagnosis in the CS database and generate remediation activities to 1) block packets from the host that triggered the attack signature detection, and in case two, the remediation action added to the database that instructs the CS firewall to impose rate limitation on the communication between the offending pair of communicating end-points. These actions are read from the CS database by the CS firewall which enforces the remediation action.

Descriptions of the methodologies and algorithms utilized

The Basic DDR delivery demonstrated the capabilities of the collection framework to collect data, for the diagnosis engine to perform very basic analysis of the data to detect relevant and actionable events, and to show how remediation activities are communicated to the policy enforcement points throughout the system. An advanced DDR capability is under development (per the original plan, this capability is constructed based on the data that is now being collected within the SGRDP). The methods for collecting, diagnosis, and remediation based on the data have been described in section 3, above, for each of the CS components participating in the data collection.

Summaries of the results of the performance of the smart grid systems and technologies derived from lab tests, field tests, or grid-connected applications

1. A demonstration of the basic DDR components of the SGRDP was performed in June of 2014. Performance of the DDR components was sufficient for the demonstration, but we were not seeing live data at that time (note that there were issues with the performance of the wireless network used to show the demonstration). Since the system has become operational we have not observed any performance issues. We have observed issues with the loss of subscriptions to the AMI and CGNMS collectors, and have addressed these issues through the addition of a server process that monitors for loss of data and submits a re-subscription request in response.

Summaries of the results of the analysis and benefits

1. The data collected has been sufficient to demonstrate the basic DDR activity within the SGRDP. We have had limited success in coordination with the other teams to obtain data from their hardware components, despite having provided them with software to collect the data from their servers. An earlier system integration effort would have greatly assisted us in this regard.

Summary of the major findings and conclusions including lessons learned and best practices.

The system is operational but we only have access to data from the operational system over a short timeframe. Additionally, the visibility of the SGRDP components to potential adversaries has been limited until recently, and we have not yet observed attacks directed to the infrastructure. As development of advanced DDR capability continues we anticipate that there will be additional sources of data needed for differential diagnoses, etc. These will constitute lessons learned, and will result to updates for the basic collection components.

Summary of future plans and next steps with respect to additional testing, demonstration, or deployment

Per the original plan, continued work on the DDR activity will encompass development of advanced detectors, diagnosis, and remediation components that deprive situational awareness of the system as a whole based on the data that has been collected using the infrastructure described herein. As we see attacks and failures in practice, we anticipate that there may be additional information not currently in our data sets, which are needed to support differential diagnoses, etc. As such additional data is identified, the detection component will be extended if necessary to obtain the additional inputs.

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A. DDR Delivery Description (March 2014)
B. CS DDR March Delivery Demonstration Host and Network Infrastructure DDR

LADWP Smart Grid
Regional Demonstration

Cyber Security (CS) Document

DDR March 2014

Delivery Description

Version 1.4

Date	Version #	Reason for Change(s)	Author(s)
2/28/2014	1.0	Imported materials from previous overview document, and added notes from 2/28/2014 meeting	JPL CS team
3/26/2014	1.1	Updated to reflect recent changes.	JPL CS team
3/28/2014	1.2	Updated to include more contextual info.	JPL CS team
6/3/2014	1.3	Updated with more detailed scenarios	BCN
6/5/2014	1.4	Reviewed, updated formatting, removed fig. 3	Gaurav M

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1. Introduction

1.1 Objectives

The purpose of this document is to describe informally the part of the DDR March 31, 2014 delivery that be used for demonstration.

1.2 Summary

The March 31, 2014 DDR delivery demonstrates a simple, operationally relevant scenario for DDR execution. This shows that both a basic DDR design and a deployment infrastructure are in place, upon with more sophisticated detection, diagnosis, and remediation capabilities can be built. The delivery demonstrates representative flows of data through the system.

The delivered software executes within the SGRDP computing infrastructure at LADWP. Figure 1 is the component diagram representing the SGRDP, which provides the context in which DDR functions. The CS components are shown in blue. The lines of communication between the components are also shown.

The DDR March 31, 2014 delivery has the capability to:

Basic Cyber DDR:

- Obtain records of detected network events incident to the CS Firewall.
- Store those records in an operational DDR database.
- Obtain CPU, network, and other system status from CS monitored components, including firewall machines.
- Store the status information in an operational DDR database.
- Perform detection of network and host anomaly events.
- Implement simple remediation actions to block certain events or to mitigate the impact of such anomalies, in response to detected network and host anomaly events.
- Provide a simple way to visualize the processing and data flow for the sample scenario, and display detected events.

Basic Cyber-Physical DDR

- Connect to the operational AMI Data Collection Engine (DCE) running at LADWP to obtain meter usage data from AMI meters.
- Store that operational meter data in DDR database.

- Generate simulated meter data and store that simulated meter data in the DDR database.
- Perform detection of real and/or simulated “meter data anomaly” events from the real and/or simulated meter data.
- Provide simple visualization the processing and data flow for the sample scenario, and display detected events.

The top-level data flow for demonstration scenario is shown in Figure 2.

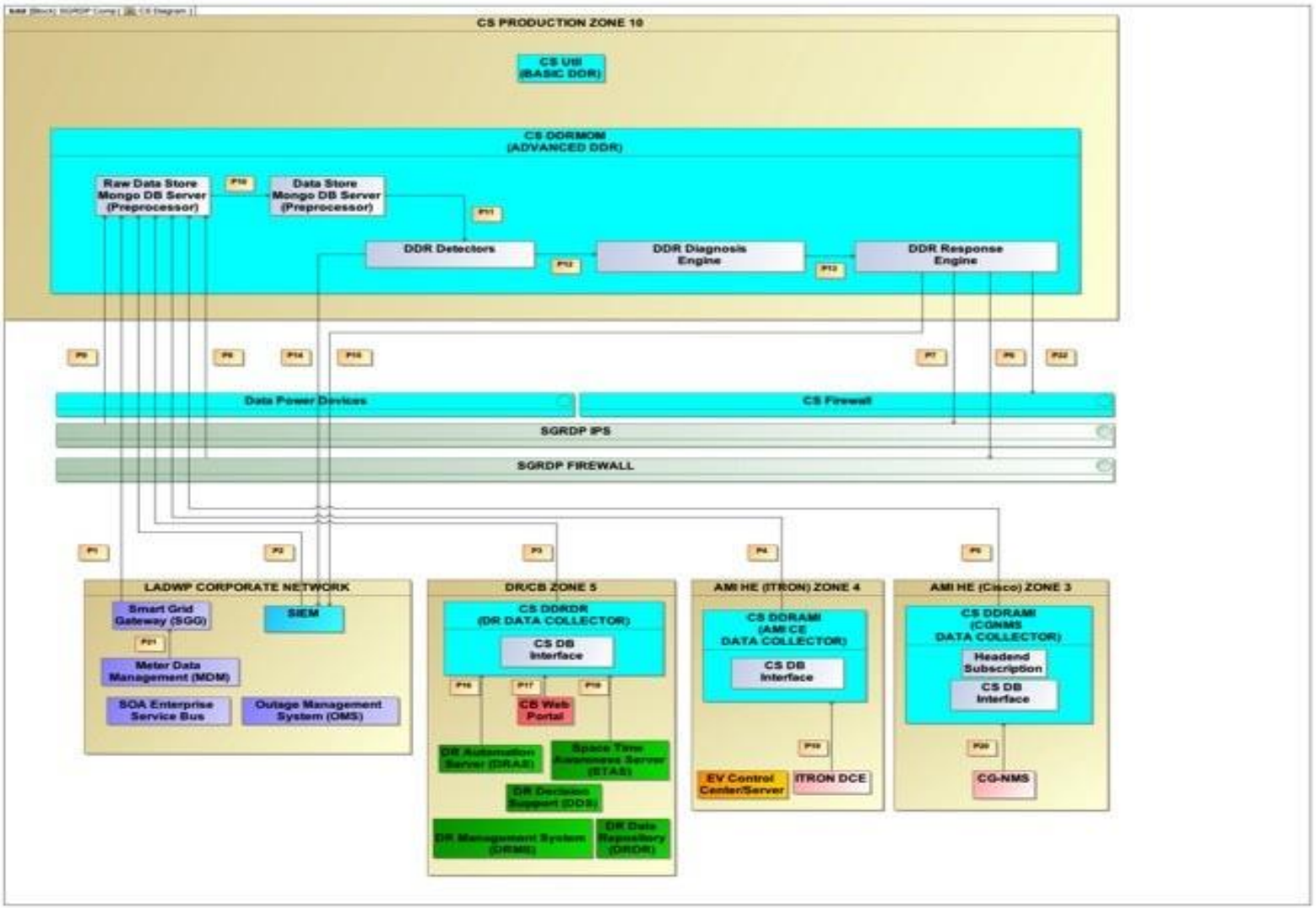


Figure 1: SGRDP Context for DDR

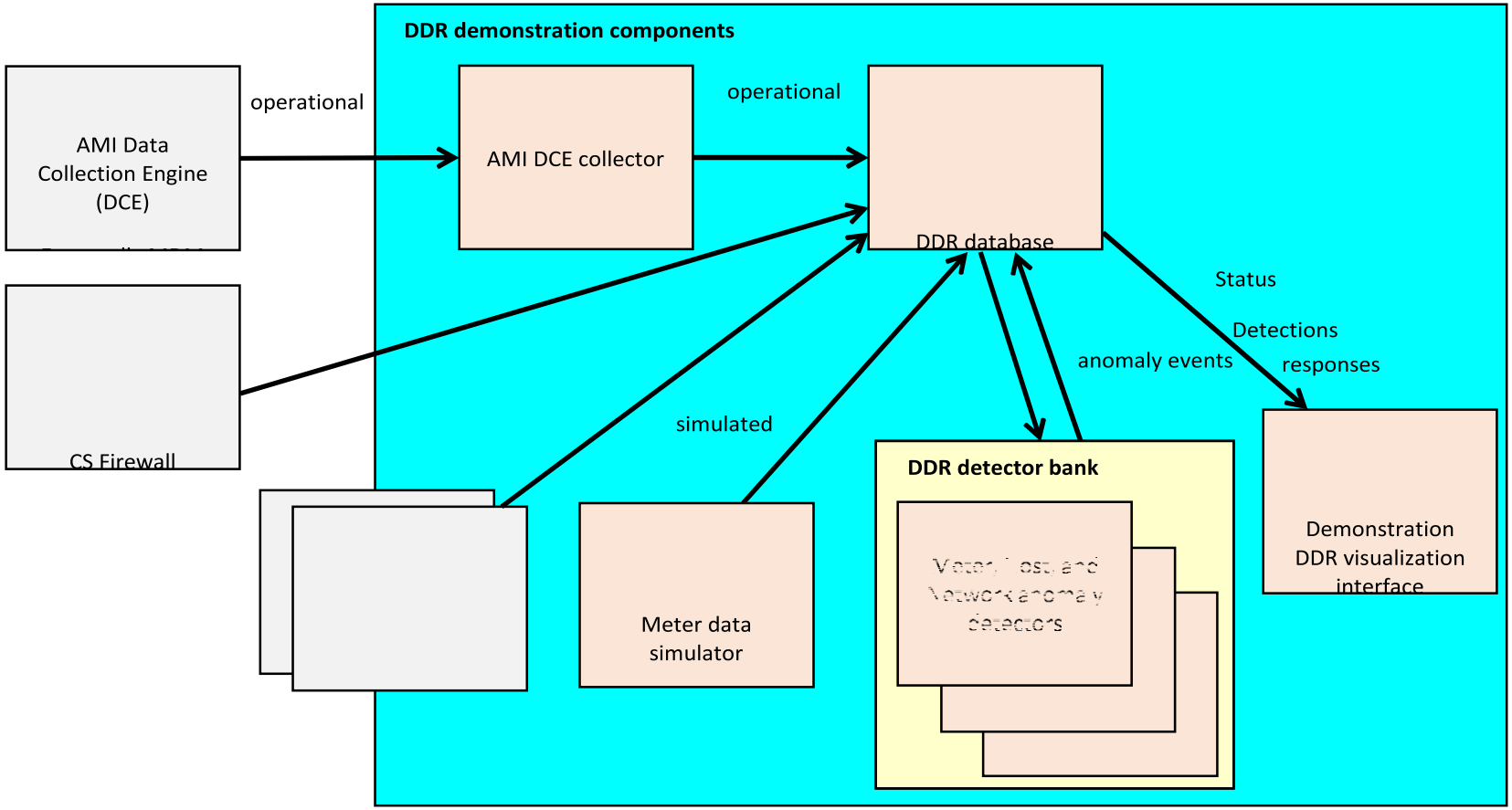


Figure 2: DDR Data Flow for Demonstration

2. Sample Cyber-Physical Scenario Energy Theft

Energy theft is identified as a key scenario in the CS demo matrix (labeled *DDR-Energy-Theft- AMI*). The March 31 delivery focuses on a subset of the functionality required to support the identification of energy theft that is accomplished by cyber-attack.

Energy theft test scenarios have been constructed with a baseline data set to inject each of the above conditions at a fixed time in the dataset:

- Baseline: Average daily profile with no energy theft injected.
- Scale factor: Usage measurements scaled to a percentage of actual usage.
- Constant bias: Usage measurements shifted by a constant value.
- Clipped profile: Usage measurements capped at a maximum value.
- Flat profile: All measurements set to a constant value.

Test data sets containing one month of usage data, including an injected energy theft, were generated from analysis of production usage data, and then modified for use in test. Fixed files were then produced that will be read into the meter data simulator, and played back into the database, per the flow in Figure 2. For each case, there is one injected anomaly (the sudden change from baseline behavior to theft-like behavior). Detector performance is measured by whether it is able to detect the injected shift in behavior, and by the number of false alarms it raises.

Testing of the infrastructure (data flow, record generation, etc.) benefits from more than one detection event per test, so there will also be test cases where the detector is tuned to generate a large number of events that would be considered false alarms.

2.1 Energy Theft Scenario

The goal of a malicious customer in stealing energy is to have the system report fewer watt- hours than the customer uses. As computing devices, smart meters provide new software- based paths to accomplish that goal. They also allow finer insight into the state and performance of metering, which can be used to detect a condition that may signal ongoing energy theft. By monitoring meter consumption data alone, it is possible to identify changes in the behavior of consumption measurements that may be symptomatic of energy theft. Energy theft scenarios that involve a compromise of the meter to modify the software behavior are considered the primary cases within this scenario that are in scope for the CS effort. The following behaviors in usage measurements are derived from an analysis of attack vectors through the meter itself.

A particular concern in detecting energy theft is that the apparent symptoms of it may actually be result of benign changes or variations in customer behavior. Because of this, detection of sudden changes in meter behavior are marked as *meter data anomalies* (not energy theft) that can then be investigated by the utility, or sent to (yet to be implemented) diagnosis routines that will correlate meter data events with other system events to increase confidence that a particular event is relevant.

2.2 Meter Data Anomaly Detection

This sample scenario describes activities that might occur that result in the identification and display of a *meter data anomaly (MDA)* event, such as possible energy theft as described above, by DDR.

The key source of data for this scenario is the AMI Data Collection Engine (DCE). The DCE provides the back-office interface to the Itron Advanced Metering Infrastructure (AMI). DCE specifically provides meter-related data via a web services interface. Client programs subscribe to data if interest, which are then pushed to clients as they are received by DCE.

The DDR AMI DCE interface software subscribes to meter usage data for meters. As it receives data from a meter M, the client writes the data to the DDR database. A DDR MDA detector obtains current and historical usage data for M from the database. Using its detection algorithm, it compares current and historical usage for M to identify potential MDAs for M. When it detects a possible MDA, it generates an event describing what it has detected and writes the event to the DDR database. The DDR GUI obtains events, including MDA events, from the DDR.

3. Sample Network Host (Cyber) Scenarios

Responding to cyber-attacks is a key scenario in the CS demo matrix. Cyber-threats include denial of service attacks on smart grid infrastructure, to prevent demand response and other commands from being implemented as needed to maintain operational resiliency of the power grid, as well as targeted penetration attempts on public facing smart grid components, and through multiple stage attacks on internal components. Diagnosis and remediation of such attacks requires collection of information on the baseline operation of the system, which will be collected once the system is operational. The basic DDR components delivered in the March release provides the basic framework into which advanced detectors, and diagnosis and remediation capability will be deployed. Three basic cyber-threat DDR capabilities are included to demonstrate the operation of the framework, and are to be demonstrated.

3.1 Detected Attack Packet Scenario

This scenario describes activities that occur as the result of the monitoring of packets at the CS firewall that match pre-specified attack signatures. It demonstrates capabilities that will apply also in later advanced DDR scenarios to signatures and anomalous activity detected over multiple sources of network monitoring, including the CS firewall, and host-associated firewalls across the protected hosts in the SGRDP.

The key source of data for the basic scenarios is the monitoring component of the CS firewall, with records of traffic matching pre-specified filters communicated to the DDR database. Of the traffic matching pre-specified filters, some subset of the filters will trigger an autonomic response on the firewall itself, in addition to sending data to the DDR database.

The DDR Cyber Detector component (initially deployed on the same machine as the CS database, but eventually running on a separate VM within the CS zone), subscribes to events from the CS database generated by the Network and Host monitors. Upon detection of attack signatures, the remediation engine generates remediation rules to block traffic from specified addresses, and those rules are inserted into the CS database. The deployed firewall components (for now the CS firewall, but eventually any host based firewalls as well) subscribe to the updates placed into the CS database by the remediation engine, and implement the change to their policies, blocking further packets from the detected source of the attack.

A visualization tool will enable the demonstration of the receipt of packets matching pre- specified signatures, as well as the change to policies which are implemented and enforced at the firewall. Demonstration of this scenario will be based on the generation of packets outside of the DWP network, destined for SGRDP hosts, with signatures matching pre-specified rules which will trigger the remediation activity.

3.2 Internal DoS - Rate Limitation Scenario

This sample scenario describes activities that occur as the result of the monitoring the data rate between pairs of communicating entities within the SGRDP. The scenario will be demonstrated on flows into the CS database from the components collecting AMI, firewall, and host monitoring data. The rates of data transmission across the CS Firewall boundary will be monitored to generate baseline minimum flow rates, and the system will be configured to enforce a maximum flow rate. Deviations from this interval will be flagged and communicated to the CS database.

The DDR Cyber Detector component (initially deployed on the same machine as the CS database, but eventually running on a separate VM within the CS zone), subscribes to events from the CS database. Events indicative of flows less than the established minimum expected rate will trigger detection of host

or network problems, and an alert will be generated and stored in the CS database, with such alerts subscribed to by visualization and network monitors. A

record indicating that the maximum flow has been exceeded will result in a similar alert stored in the CS database, as well as the generation of remediation actions, also stored in the CS database. The remediation records are subscribed to by the firewall, which can enforce the remediation action, which may require changes to enforced rate limitation on the flows between the particular pair of entities. Prior to the change in rules, the firewall will astronomically impose rate limitation based on a pre-configured limit on the flow rate.

Demonstration of this scenario will occur by creating additional sources of (dummy) events to be placed in the CS database, such that the source of dummy events will exceed established limits. The firewall will clamp down on those flows sufficiently to allow the CS database to continue processing flows from the other (non-compromised) sources. This capability improves the resilience of DDR to denial of service that would otherwise occur if any of the monitors (present on machines outside the CS zone) were to be compromised. The capability is more generally useful to prevent denial of service attacks on other components within the SGRDP, including CB and DR resources.

3.3 Compromised/Runaway Process Scenario

This scenario describes activities that occur as the result of the monitoring of system resources and processes on monitored and protected machines. In the demonstration, the monitored and protected machines are the CS database, the CS Firewall, and possibly the AMI and DR collector machines.

Monitors on protected machines generate event records with information about process creation, resource utilization, and system load, which are sent to the CS database. The DDR Cyber Detector component (initially deployed on the same machine as the CS database, but eventually running on a separate VM within the CS zone), subscribes to events from the CS database. Events indicative of contention for system resources trigger an assessment of the consumption of individual processes. If an individual process is determined to be consuming significantly greater resources than is normal (an anomaly condition), a remediation record is generated alerting operators to the problem. The monitors on the protected machine subscribe to remediation records regarding their own activities, and the generated record will result in remediation action initially re-nicing the offending processes, but in advanced DDR, this action may result in restarting or terminating processes as well.

4. Key DDR Components

4.1 AMI Data Collection Engine (DCE) Interface Software

The AMI DCE interface software subscribes to the DCE for meter-related data of interest, receives the data from DCE, and writes the data to the DDR database.

4.2 Meter Data Simulator

The meter data simulator generates simulated meter data. This functionality is required during subsystem testing. The simulator is used to create data containing simulated anomalies, statistically significant larger data sets, a fault-injected test corpus, etc.

The output format for the simulated data is the same as the format of the data generated by the AMI DCE interface software, except that there is indicator flag in each record indicating whether the source is the AMI DCE interface software or the meter data simulator.

4.3 DDR Database

The DDR database is the central repository for data received by DDR, as well as other data generated by DDR internally (e.g., detected events).

4.4 Meter Data Anomaly (MDA) Detector Bank

The MDA detector bank is designed to contain a diverse set of detectors. The detector bank obtains data (*e.g.*, meter usage data from the DDR database) after which each detector, or combination of detectors, will analyze the data to detect potential MDA events. The infrastructure is designed to be flexible, in that it allows the incorporation of new detection algorithms that may be better suited to new and evolving threat scenarios. The detector bank writes detected events back to the DDR database.

4.5 Network and Host Anomaly (NHA) Detector Bank

The network and host detector banks are designed to contain a diverse set of detectors. The detector bank obtains data (*e.g.*, network rates, packet summaries, log data, host statistics from the DDR database) after which each detector, or combination of detectors, will analyze the data to detect potential network and host anomaly events. The infrastructure is designed to be

flexible, in that it allows the incorporation of new detection algorithms that may be better suited to new and evolving threat scenarios. The detector bank writes detected events back to the DDR database. At present, the detector is also capable of writing simple scripted remediation commands to the DDR database, though this functionality will be moved to a separate remediation component in advanced DDR.

4.6 DDR Visualization Interface

The DDR visualization interface obtains events of interest from the DDR database and displays them to the user. While a basic visualization interface is provided within the DDR itself, it is expected that visualization will utilize more flexible visualization tools from the SIEM.

Appendix S Integration of SGRDP Containment Capabilities into SGRDP



Cyber Security (CS) Document

Integration of SGRDP Containment Capabilities into SGRDP

Version 1.0

Date	Version #	Reason for Change(s)	Author(s)
2014-08-15	0.1	Initial draft outline	JPL & ISI CS teams
2014-08-31	1.0	Initial release of document	JPL & ISI CS teams

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APPENDIX **8**

OVERVIEW

Smart grid capabilities and functions demonstrated

This demonstrates the ability to manage and control the flow of data across zones within the SGRDP and to and from sites external to the SGRDP, according to defined policies and to protect the integrity of systems and data within the SGRDP.

Smart grid impacts and benefits demonstrated

Protection of the SGRDP depends on the capability to prevent the propagation of attacks, and to prevent infiltration and exfiltration of data contrary to policy. The containment capabilities ensure that only defined and authorized communication occurs between components of the SGRDP, and are critical tools to protect the integrity of the system and to prevent exfiltration of sensitive data contrary to defined policy.

List of objectives/Scope

The objective is to constrain the communication between SGRDP components and to and from external systems so that only communication specifically required in the system design is authorized.

Mapping to the SOPO & Deliverables

The integration and deployment of containment technologies within the SGRDP supports CS Demonstration 3, "a demonstration of the ability of the smart grid infrastructure to limit the flow of customer and system data according to defined policies and to protect the integrity of the data [and the system]".

CHARACTERIZATION OF BASELINE SGRDP SYSTEM

An understanding of the baseline SGRDP design provided the basis for drawing the initial SGRDP fault containment regions (FCRs).

Identification of equipment and functions

The SGRDP has five components: AMI, CB, CS, DR, and EV. As the other four components provided design information to CS, we captured and diagrammed their expected functions and associated equipment. The groupings constrained choices for containment boundaries.

Analysis of data flows

We then analyzed the key data flows among the components, equipment, and functions, and identified the interfaces and dependencies.

CS feedback to modify design

We recommended some specific changes to de-couple functions that did not have a real need for the dependencies that were initially designed in, and to re-route some data flows to separate sensitive functions from potentially "dangerous" sources. For instance, rather than placing a database server directly on the external internet, CS recommended the use of a proxy server for the external-facing functions to separate them from sensitive internal communications and data.

DEFINITION OF BASELINE FAULT CONTAINMENT REGIONS (FCRS)

"The primary goal of a FCR is to limit the effects of a fault and prevent the propagation of errors from one region of the system to another. A FCR is a subsystem that will operate correctly regardless of any arbitrary fault outside the region." *A Primer on Architectural Level Fault Tolerance, NASA/TM-2008-215108*

Our analysis of the baseline SGRDP system and its functional relationships led to a definition of an initial set of FCRs. The FCRs are shown in Figure 1 as black outlined zones around sets of equipment and functions.

Thus, for instance, we recognize that a fault in a customer residence (FCR 5) need not, and should not, impact the DR Web Portal (FCR 4). Whether that turns out to be true in practice depends on the implementation of protection layers between the FCRs.

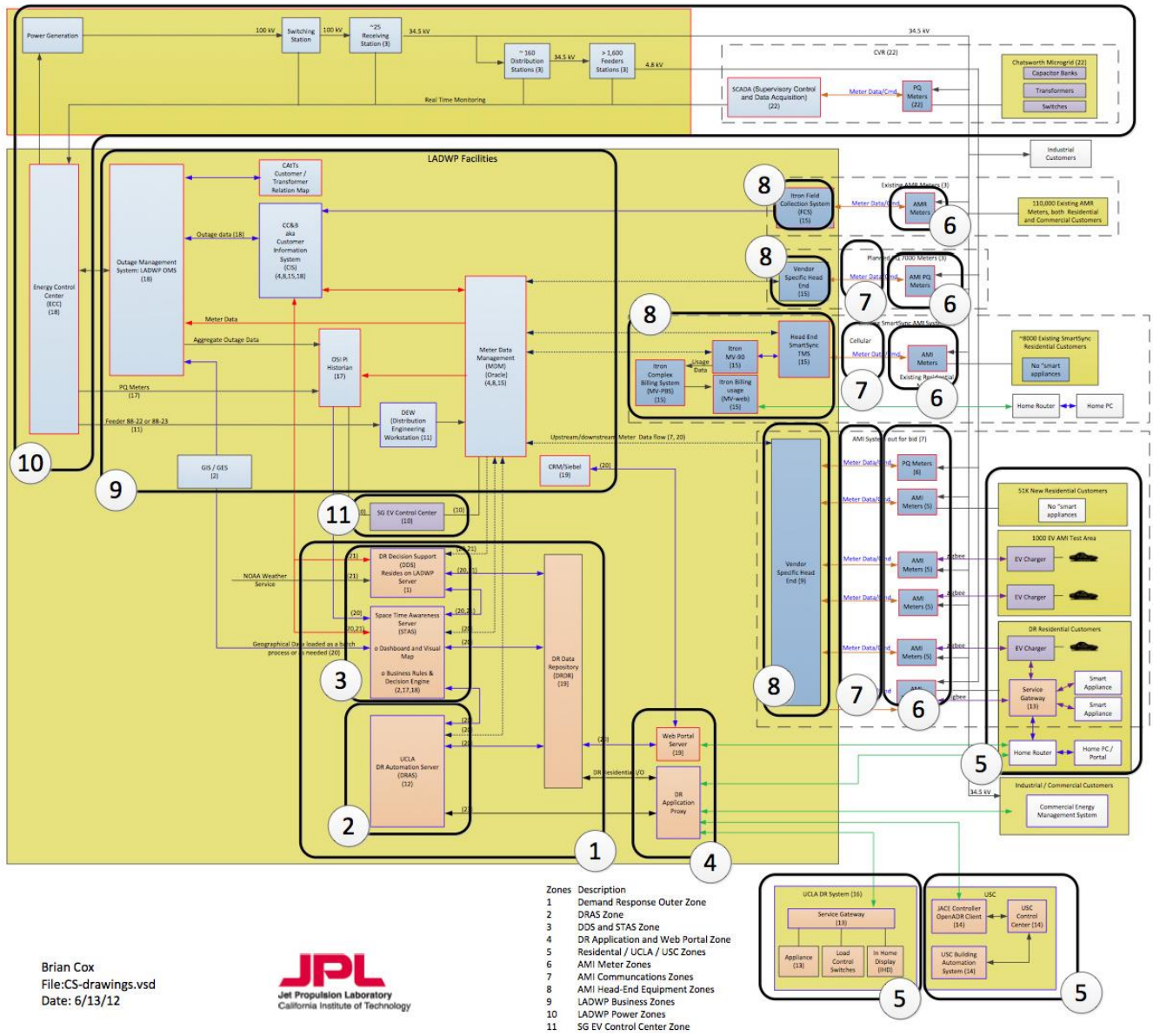


Figure 1: FCR Boundaries

TECHNOLOGIES AND SYSTEMS USED IN THE DEMONSTRATION

The existing network infrastructure of the Los Angeles Department of Water and Power (LADWP) includes the use of multiple firewall and intrusion prevention systems.

Containment within the SGRDP, in support of the communication identified in the earlier fault containment diagram, is implemented through five technologies described in this section.

Definition and deployment of Virtual LANs (VLANs)

Following the philosophy behinds FCRs, the LADWP network engineers created a collection of virtual local-area networks (VLANs) to host SGRDP equipment. These are shown in Figure 2. The VLANs are connected to the existing corporate network through a firewall. Within each VLAN (that is, among the systems within an SGRDP component or set of closely related functions), communications are unrestrained.

Between VLANs, the connecting firewall is configured to limit communication to that which matches the flows between the FCRs identified as needed in the system design. The matching is shown in Figure 3.

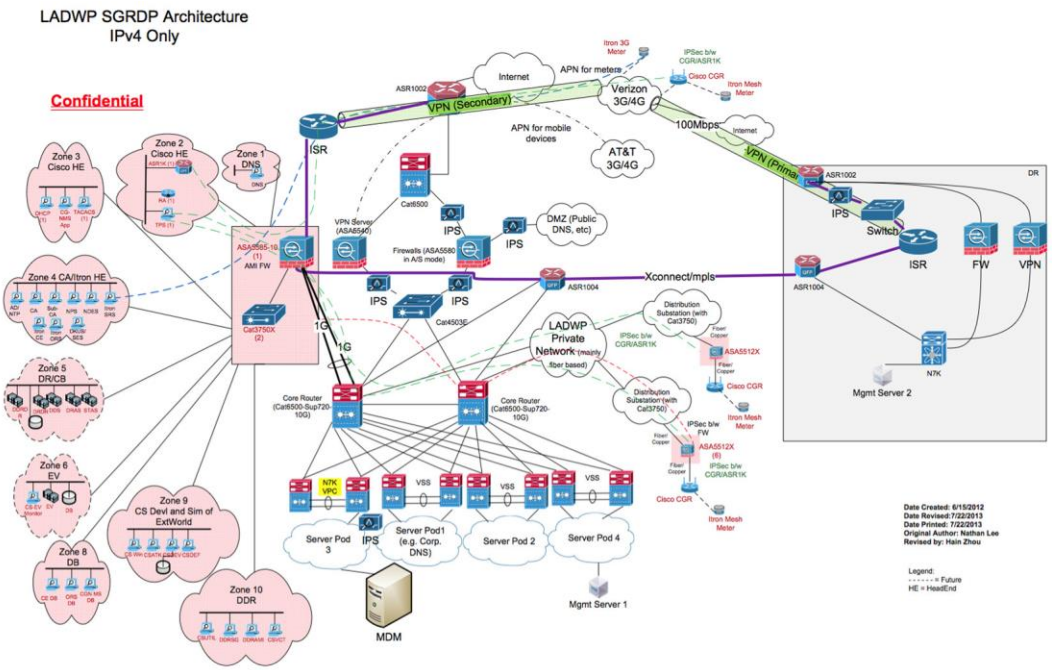


Figure 2: VLAN Architecture

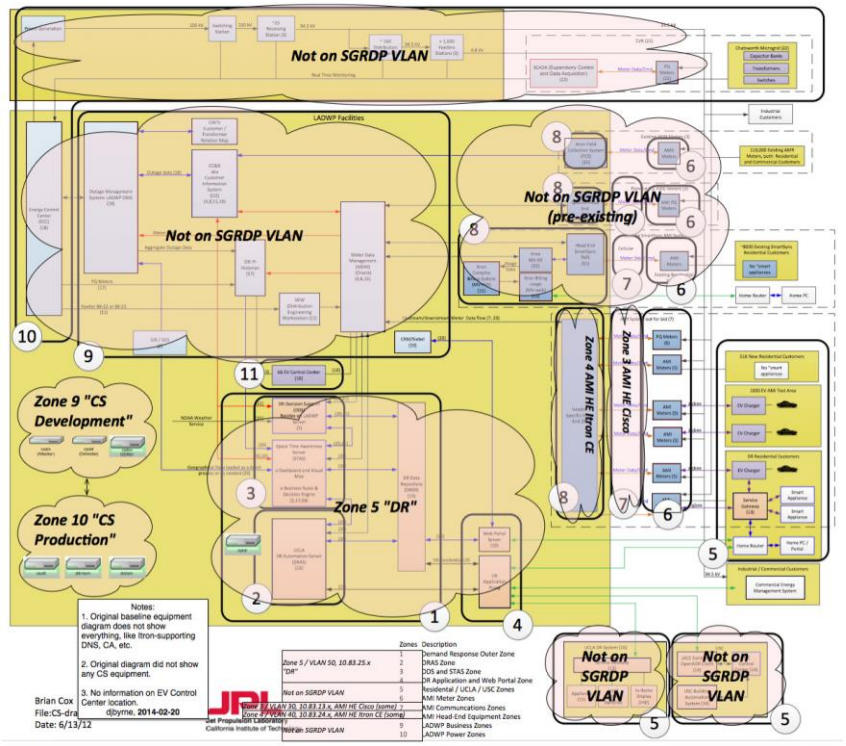


Figure 3: Mapping between FCRs and VLANs

AMI tunnels

Communication between the AMI meters and the head end originates at the meters, flows through one of several communication technologies (mesh, cellular), may be consolidated through Cisco Connected Grid Routers (CGRs), and is communicated into the core of the SGRDP network through virtual private networks (also referred to as tunnels). This technology protects the integrity and confidentiality of the communication, and provides containment of the communication traveling through the tunnel, preventing injection of unauthorized traffic into the SGRDP, or exfiltration of unauthorized traffic out of the SGRDP. These tunnels are shown on the VLAN network diagram above.

CS firewall

In addition to the firewalls deployed within the LADWP network infrastructure, flows of data across SGRDP domains, as well as data flowing into SGRDP domains from the internet, will be controlled by one of the CS Firewall or the DataPower appliance.

The CS Firewall collects additional data about traffic crossing domains, including the monitoring of the quantity of data, and the inspection of traffic for known attacks and anomalies. Detected events and statistical information is written to the CS DDR database. The CS firewall also accepts dynamic remediation actions from the DDR part of the system and implements those actions to block traffic that has been identified as an attack, or to rate-limit pairs of communicating end-points to mitigate the impact of denial of server attacks or runaway processes.

DataPower application-layer firewall

The DataPower appliance (of which one is currently deployed) is an application-layer proxy/firewall which accepts data transmitted from the collection engine, from Demand Response, and from the Meter Data Manager (MDM) (in the corporate zone) and relays those commands, and the data in response, to the other connected end points. The DataPower device has been programmed to limit the flow of data to pre-defined data formats that are authorized to flow across the defined boundary, providing protection to the LADWP corporate zone from activities in the smart grid zones. This is critically important because only parts of the LADWP corporate zone databases are relevant to the smart grid, and application-layer isolation is provided by the DataPower appliance.

Endpoint SSL/TLS

Communication between SGRDP end-points, including communication with customers, and "customer owned" equipment such as home gateways and appliances), is protected using secure sockets later/transaction layer security (SSL/TLS). This protects the integrity and confidentiality of data as it flows across the networks (including the internet), and provides authentication of end points: one or both, depending on the particular instance.

This part of the deployment is implemented within the endpoints provided by the various SGRDP teams, based on the requirements and guidance provided by the security team. As many of these components are presently outside of CS's direct purview, and they are still undergoing changes by their respective implementers, the extent to which this guidance has been adopted has not yet been assessed.

SUMMARIES OF THE RESULTS OF THE PERFORMANCE OF THE SMART GRID SYSTEMS AND TECHNOLOGIES DERIVED FROM LAB TESTS, FIELD TESTS, OR GRID-CONNECTED APPLICATIONS

We did some initial evaluation of how the deployment of the VLANs and firewalls realized the FCRs, and identified future steps to refine the design and deployment.

In the demonstration provided in June, performance of the containment technologies was sufficient, but further evaluation and stress testing is warranted as the traffic flowing across regions grows during continued operation of the SGRDP.

SUMMARIES OF THE RESULTS OF THE ANALYSIS AND BENEFITS

Analysis is pending based on a threat assessment and penetration tests that are still being planned.

SUMMARY OF THE MAJOR FINDINGS AND CONCLUSIONS INCLUDING LESSONS LEARNED AND BEST PRACTICES

While we have been able to assess the effectiveness of the technology for communications with the computer security components, the limited system integration activities that have occurred so far have prevented us from properly assessing the application of these technologies where deployment on machines for the other parts of the SGRDP require modification and monitoring. An earlier system integration activity would have been beneficial. Those activities are now in process.

SUMMARY OF FUTURE PLANS AND NEXT STEPS WITH RESPECT TO ADDITIONAL TESTING, DEMONSTRATION, OR DEPLOYMENT

A threat assessment is planned, under which all communication end points will be enumerated, and the specific required and deployed containment mechanisms identified. This will include the mechanisms that were specified for end-points on non-CS SGRDP machines to make sure the required mechanisms are in place.

Additional penetration testing of the system is planned.

APPENDIX

Detailed Demonstration Matrix - Including demonstration details, input, outputs and result:

(This is a report of the deployment of a system that constitutes a part of the demonstration. Results of the demonstration will not be available until further data is collected from the fully integrated system).

Appendix T Technology Performance, Security and Containment Assessment, and Pen Testing Guidance

LADWP Smart Grid Regional Demonstration Program

Cyber Security (CS) Document

Technology Performance, Security and Containment Assessment, and Pen Testing Guidance

Version 3.4

Date	Version #	Reason for Change(s)	Author(s)
4/20/2016	1.0	Initial Revision	USC
5/04/2016	1.1	Added additional information on zones	USC
5/25/2016	1.2	Completed report for review	USC
6/15/16	2.0	Merged Pen Test Plan	USC
6/23/16	3.0	Edits based on feedback from earlier versions	USC
6/29/16	3.1-3	Fix references and finalize	USC
7/6/16	3.4	Added Lessons Learned	USC

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Overview & Description

The purpose of this document is to evaluate the performance of the technology deployed by the Computer Security group as part of the Los Angeles Department of Water and Power Smart Grid Regional Demonstration Project (SGRDP). An important component of the performance evaluation lies in assessing the conformance of the SGRDP deployed components (including the non-security components) to the security requirements identified during the requirements phase of the program, and in particular to the objectives identified in the Cyber Security sections of the Security and Interoperability plan. In so doing, this will highlight susceptibility of the SGRDP components to and resilience against evolving threats. As a demonstration project, certain security technologies were included in the design of the project – some of which have performed as expected, and some of which were less effective for a variety of reasons. This report will discuss the effectiveness of the technologies included in the design. Where certain technologies were not effectively deployed, the reasons will be discussed and lessons learned provided. Where technologies were effectively deployed, the impact on the security of the system will also be discussed.

As part of the assessment, this document also provides guidance for the fully scaled deployment of security technologies for the Los Angeles Department of Water and Power and it highlights capabilities that were identified through the demonstration deployment, but which were not deployed.

Finally, the document provides a plan for testing the containment and software security capabilities in the demonstration infrastructure.

Methodology

The methods used for security in the SGRDP set forth with the goals of providing protection for SGRDP deployed components; the advanced metering infrastructure, demand response, electric vehicle components and customer behavior functions across the infrastructure, i.e. this includes components deployed in systems under the physical control of the LA Department of Water and Power, components in the field, and also components on customer premises. These components of the system were to be protected against denial of service attacks, traditional cyber security penetration, exfiltration, subversion and malicious code, and new forms of cyber physical attacks.

These security requirements were met during development and deployment of the SGRDP through a combination of careful architectural design for the SGRDP in combination with the deployment of traditional IT security capabilities and new approaches to security focused on the cyber-physical characteristics of the system and attacks, and finally through new cyber-physical capabilities developed for detection, diagnosis, and remediation.

The solutions applied from classic cyber security include deployment and use of existing DWP infrastructure for Authentication and Identity Management, including containment technologies, firewall configurations, and VLANs. The goal was to leverage those technologies already deployed and also to deploy new infrastructure specifically within the smart grid domain.

Deployment of the containment technologies was guided through smart grid specific architectural development including the definition of protection domains guided by the functional and authorized information flows necessary to meet the policy requirements for confidentiality, privacy, integrity and resilience for the smart grid. Because of the cyber-physical nature of the system we described these domains throughout the architecture as fault containment regions. Several layers of firewalls and routing technologies were deployed to enforce the information flow policies across domains.

During the deployment of the SGRDP, special focus was paid to system integrity. For the Advanced Metering Infrastructure (AMI) components of the system, requirements were imposed on the vendors to verify updates to software and configuration of meters through a digital signatures applied by the utility. With respect to other software components of the SGRDP, end systems are instrumented with an integrity monitor that utilizes Another File Integrity Checker (AFICK) tool to communicate the checksums of all new and changed software components to the detection, diagnosis, and remediation database within the security component of the SGRDP. Changes are authorized by consulting a policy database of allowed software components maintained within the DDR mechanisms, and any changes not authorized result in a diagnostic event that is generated and presented to operators through the Security Information and Event Management (SIEM) system.

System compromise typically involves altering system files therefore the integration of the file integrity checkers is an important capability in intrusion detection, diagnosis, and remediation. The goal of this effort was to design and develop a policy based integrity tool that monitored integrity of the SGRDP system components, detected unauthorized modifications, and communicated changes to the CS zone. One of the challenges in using an integrity checker is the false positive problem. When one updates software components or applies system patches, this changes guarded files and generates alerts. Maintaining the database of signatures is not easy. The deployed integrity checker tool addresses this issue by supporting whitelist policies that contain a list of files and directory changes which should be ignored. Additionally, the whitelist contains signatures (digital fingerprints) for authorized objects. The integrity checker invokes AFICK, consumes its report, applies whitelist polices, creates its own report and forwards it to DWP MongoDB.

The fingerprints of new software components (including changes to the components) as well as configuration files are compared with authorized fingerprints, and changes that are not in conformance with the policy result in a diagnosis event and an alert generated through the SIEM. The updates to the CS DB are monitored by the CScomponent_monitor that detects events of interest and sends them to the SIEM service running on a host in the SGRDP testbed at DWP. During the deployment of the integrity checker, we found that the CScomponent_monitor was developed with a pre-defined fixed set of events to monitor and report and required integration with the integrity checker. To enable propagation of the integrity reports to SIEM, we modified CScomponent_monitor code to accept integrity checker events.

Initially, the whitelist policies specified objects (files and directories) to be monitored and objects that can be safely ignored. This approach largely duplicates the AFICK configuration settings. The whitelist is used primarily to filter benign changes that are not to be reported as diagnosis events. In the current implementation, the whitelist contains directories and files that are ignored as well as fingerprints of

authorized objects. If AFICK detects a change, but the observed fingerprint matches one authorized in the whitelist, the change is not listed in the diagnosis report.

The integrity checker has been designed, implemented, tested on Linux and Windows platforms and installed on the DWP testbed and is in operation. The tool was demonstrated (integrity checking as visualized through the SIEM) to DOE on December 8th, 2015.

Among the tools specifically developed to address the cyber-physical nature of threats to the SGRDP was the cyber and physical detection, diagnosis and remediation (DDR) component of the system. This component focused on attacks against both the IT and the physical infrastructure of the system. The DDR mechanisms accept input from traditional computing components such as firewalls and intrusion detection components. It combines this information with physical inputs regarding load curtailment events and interval load measurements from deployed AMI meters. Data is correlated to filter out changes due to the expected behavior of the system, and alerts generated for detected penetrations as well as anomalous physical readings that are indicative of energy theft, coordinated physical attacks, and in many cases component failure.

The system generates situational awareness that is used to detect changes in the physical characteristics of the system that identify cyber-physical attacks that manifest at the edges of the system – and where the cyber component of the attacks may be in the unmanaged customer part of the system. The situational awareness of the physical state of the system will eventually be used to assess candidate remediation actions designed to bring the system back to a more resilient state.

Components to be evaluated

The DWP Smart Grid cyber infrastructure comprises components supporting the Advanced Metering Infrastructure, Demand Response, Electric Vehicle, Customer Behavior, and Computer Security. It also touches upon and depends upon certain enterprise communication and computing infrastructure, and physical infrastructure used in the generation, distribution, and use of energy. These components are deployed across 11 fault containment regions in the smart grid architecture. The security, resiliency, and privacy requirements identified during the requirements phase of the project are to be evaluated for each of these components.

As identified in the demonstration matrix, some requirements are applicable only to particular components of the infrastructure. Other requirements apply to multiple components. This report will evaluate the components of the infrastructure against the relevant requirements, and it will identify the techniques that have been deployed that meet the requirement, demonstrating that the requirements have been met in the Smart grid demonstration deployment. Where testing (such as red-teaming or penetration testing) is required to validate that a requirement is met, the appropriate class of test will be identified. Where further evaluation of a component is required, the necessary evaluation will also be highlighted.

Requirements for evaluation.

A key objective of the Smart Grid project was to foster diverse grid applications and open access for their deployment, as opposed to operating within a tightly-managed and rigidly closed environment. This objective created a special emphasis on effectively addressing the problem of security and trustworthiness.

The Cyber Security Project was tasked to implement Cyber Security for the SGRDP in its entirety. Consequently, the high-level goal of the Cyber Security Project was to increase the reliability of the power system, and it was within the scope of the Cyber Security Project to make the Smart Grid more resilient to withstand attacks and failures that can be attributed to malicious as well as non-malicious sources, such as human error.

The overall SGRDP cyber security approach is best described as a "defense-in-depth" strategy where several levels of security are designed to mitigate current and new threats. However, central to this strategy was a combination of two primary facets: 1) solutions drawn from standard or "classic" information security techniques and 2) the development of the "next-generation" cyber security approaches that target major challenges that impact or are impacted by the cyber-physical characteristics of the Smart Grid.

The security requirements against which the smart grid infrastructure is to be evaluated fall into several categories. The most constructive category comprises the security requirements identified in the requirements phase, as it is applied to the relevant parts of the demonstration infrastructure, the goals of which were highlighted in the Security and Interoperability Plan approved by the Department of Energy. These are the requirements we focus on in this report. Subsequent release of this report will additionally address specific "demonstration objectives" which were created by PEPMO, based on a list of potential threats identified by the CS team during the requirements phase of the demonstration. This list duplicates many of the items from the first list and omits others, and it will be included in subsequent reports for completeness.

SGRDP Program Architecture

Figure 1 presents a layered view of a general Smart Grid architectural space comprised of: the physical power layer (transmission and distribution), the communications layer (data transport and control), and the applications layer (applications and services). In addition to the basic layering structure are renewable and distributed generation and storage options at the power layer; the emergence of home area networks (HAN) which enable smart appliances, homes and buildings; and most importantly the idea of multiple and diverse applications (the green layer) such as AMI and demand response, that are enabled once a shared, unified communications layer was established from the utility to the end-user.

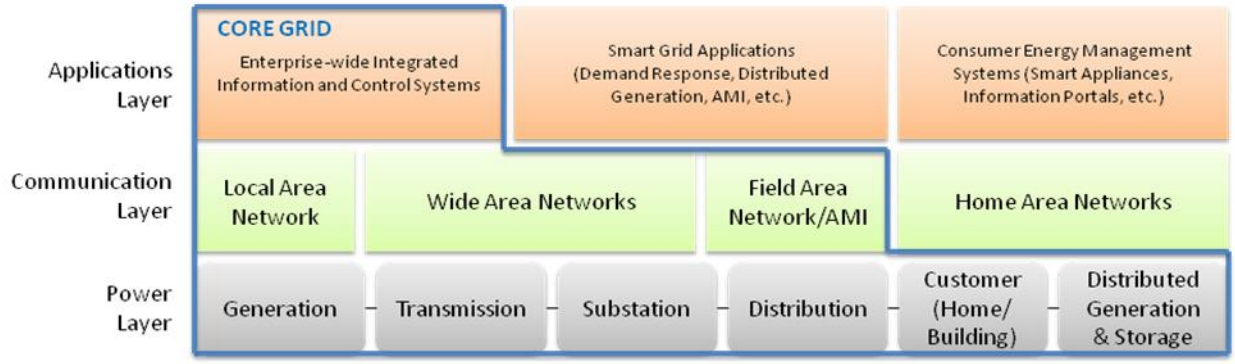


Figure 1: Smart Grid Architectural Construct Indicating Platform Boundary

Figure 1 also adds a boundary that divides the system elements into two parts. This division is referred to as the platform boundary, and refers to any architecture that exhibits the division as "platform-centric". The distinction between the two regions is one of both technical structure and industry structure, with significantly different design goals in both dimensions. Within the Core Grid platform, much of which was already in place and being operated by LADWP, requirements were developed for the SGRDP to provide robustness and stability, rational and transparent economic structure, and an open and, accessible "level playing field" for the portions of the system residing outside the platform region. The provision of highly reliable and economical electric power, and the values of neutrality, economic and regulatory transparency, and open access consistent with technical and policy requirements, are precisely the objectives of the Core Grid portion of the platform-centric Smart Grid architecture.

Outside the Core Grid, requirements support an evolving diversity of capabilities and applications, while meeting customer objectives including customization, development, and innovation. As a direct corollary of these requirements, the outside environment is more diverse and competitive. This is the region of Smart Grid applications supporting the economy of the City of Los Angeles, by meeting the evolving needs of its diverse customer base and by underpinning innovation in the delivery of advanced energy services. They are exactly the capabilities enabled within the "Grid Applications" segment of the industry by a platform-centric Smart Grid architecture.

Application Development Platform

The design, prototyping, and rollout of this integrated system addressed a variety of important objectives related to the integration of legacy information systems and physical systems into the next - generation, digital Smart Grid infrastructure including data privacy and cyber-security aspects of systems integration. With respect to security the necessary system objectives included:

A security and reliability framework designed to protect the core grid and other applications from an errant or malicious user or application developer. This framework assumes that normal end users have substantial ability to access and modify grid applications, though not the core platform. Such a framework includes both:

- Elements from traditional information security, such as authorization and access control, and
- Elements from robust system design theory, such as data validation and self-limiting control mechanisms.

An information management and privacy framework which implements functions including:

- Protecting the privacy of individual customer usage information, while providing statistically valid aggregate information for supply/demand modeling and control.
- Providing statistically valid information to grid applications for situational awareness regarding core platform conditions and performance, while addressing security and competitive concerns.
- A secure platform that allows 3rd - party applications and developers to access the system

Integrated Communications

At the heart of the SGRDP's systems integration framework is the notion of an abstract interface and data model that acts as a central but lightweight mediator of information flow between consumers and providers, while ensuring that access control policies and cyber-security measures are applied in the context of that particular transaction.

The communications and data model supports:

- The current deployment of AMI infrastructure at City of Los Angeles facilities, USC and UCLA-owned facilities: The facilities owned and operated by the City of Los Angeles and the universities utilize existing fiber optic networks for communication, as well as meters that utilizes 2-way communication and home area network capabilities.
- Integration of user-interface applications for monitoring, controlling and adjusting energy use in combination with media streams such as web and cell phone applications.
- Established charging stations with communications to the grid management system: The charging facilities utilize an existing fiber optic network; that transmits data from the meter attached to the charging station.

SGRDP Cyber Security Strategy

Deployment of the SGRDP required consideration of security throughout the lifecycle of the system. The most effective security measures are not the defenses that are bolted onto a system after the fact, but instead the security consideration that went into the architecture of the system as a whole during design. The SGRDP Cyber Security strategy is a "defense-in-depth" approach that is comprised of two core areas:

- Solutions drawn from standard or "classic" security techniques such as role-based authentication and authorization and usability-oriented security designs for consumer-level applications, and
- The development of the "next-generation" cyber security approaches that targets improving the resilience of the Smart Grid to cyber-physical attacks and faults.

The following sections describe the general principals and approaches that comprise the functional components of the SGRDP cyber security strategy, e.g., privacy and trust, data integrity and availability, secure logging and monitoring, security event response. Examples of how these have been applied to the SGRDP are described with each section.

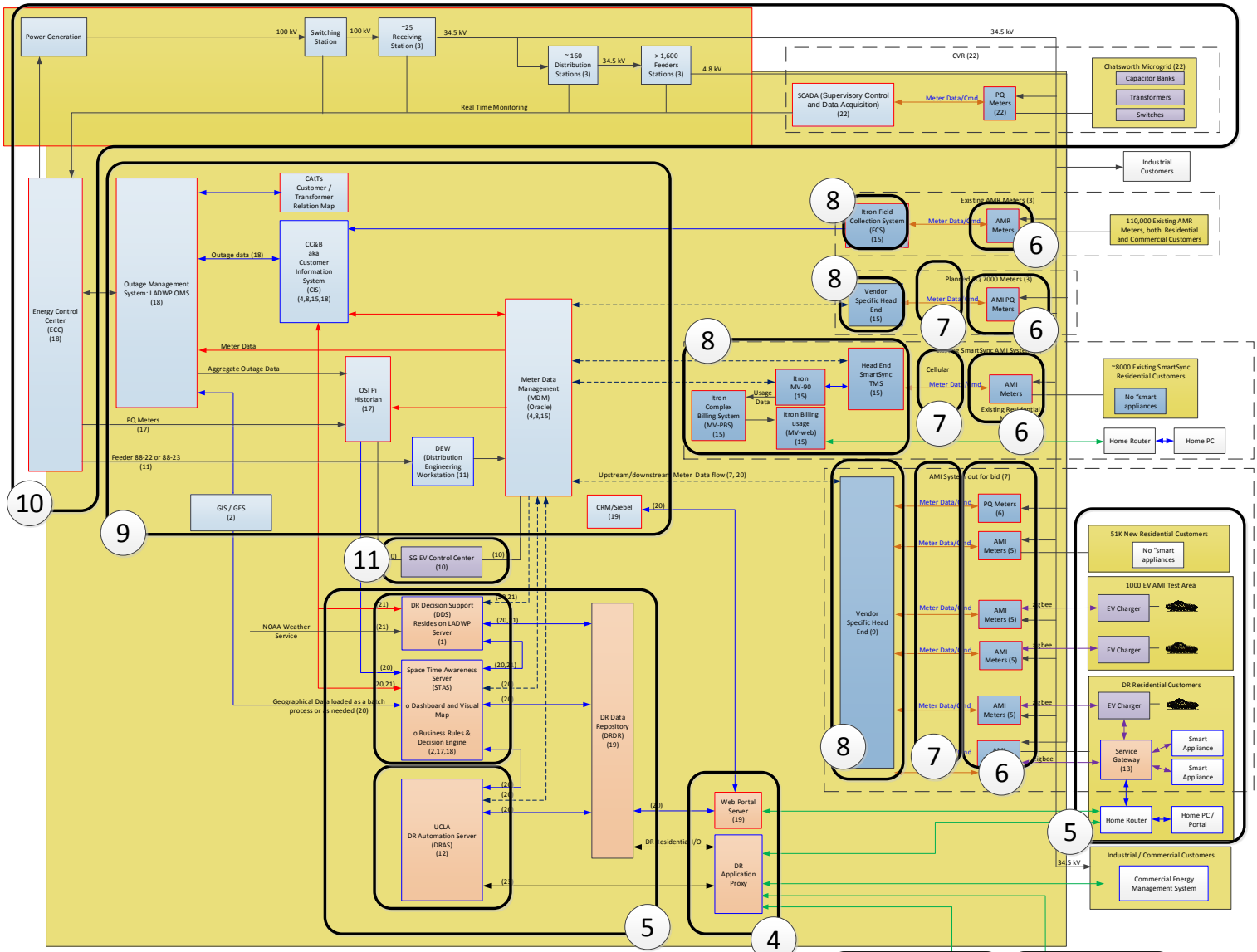
Fundamental Security Considerations for the SGRDP

Critical considerations for the SGRDP were security of the data that is maintained, where it is stored, and the control mechanisms deployed. Traditional security techniques are only effective when the data and control channels are located in areas that are securable. Within the SGRDP, an understanding of security perimeters impacted the system architecture. We divided the system into regions managed by the customer, several regions managed by the utility (e.g. those functions critical to the operation of the system, and those functions use for billing and customer information), and the open internet. Although systems in the past have tended to be implemented under an assumption of utility control over all parts of the system, this simply was not the case given the goals of the demonstration and the requirements for customer access to information and customer controls on demand. Inclusion of the internet in our consideration was necessary because customers make decisions based on information they obtain from the Internet, and their decisions impact the grid – creating a hidden control channel that must be managed.

We considered the Confidentiality, Integrity, and Availability (CIA) controls that provide resiliency in each of these regions, and looked at the mechanisms used to meet those needs. We use cryptographic mechanisms for confidentiality and integrity as data is communicated, but we also considered the physical access characteristics of the devices where the data will be stored. Resiliency and availability required redundancy and delay-tolerance (that data can be retained and transmitted at a later time). Different kinds of data have different requirements on how much of a delay can be tolerated.

The delay tolerance characteristics affected the design of the communications channels deployed for various functions, for example, a low-bandwidth, highly resilient communications method for control messages, while tolerating less reliable and less expensive channels for billing information by ensuring that devices can buffer such data long enough to recover from a denial of service attack or other problems on the billing channel.

Similar design decisions were made based on confidentiality and integrity requirements. In particular, integrity requirements dictated where certain information could be generated. Consumption information is generated at the meter, rather than in the client-controlled part of the system. This was necessary, because the customer might be an adversary with respect to the integrity of usage information. Meters are generally located on the customer's premises and there are technical integrity mechanisms that are applied to detect tampering, effectively extending the utilities security perimeter into the meter. Additional security controls include that include cryptographic attestation of the hardware, combined with tamper-residence security controls. Figure 2 below shows a diagram of the fault containment regions for the SGRDP.



Zones	Description
1	Demand Response Outer Zone
2	DRAS Zone
3	DDS and STAS Zone
4	
5	DR Zone
6	AMI Meter Zones
7	AMI Communcations Zones
8	AMI Head-End Equipment Zones
9	LADWP Business Zones
10	LADWP Power Zones
11	SG EV Control Center Zone

Brian Cox
File:CS-drawings.vsd
Date: 6/13/12

Jet Propulsion Laboratory
California Institute of Technology

Figure 2: Smart Grid Fault Containment Regions

Privacy and Trust

Customers are rightfully concerned about the privacy of their Personally Identifiable Information (PII), and they require trust in the integrity of the data upon which their bills are generated, and which may at their request, be provided to them or to third-party services of their choice. They also require trust in the proper and secure operation of the smart grid, especially with respect to signals that might affect the operation of their own equipment (e.g. demand-response or pricing signals).

These issues were addressed throughout the entire SGRDP design and implementation, from the encryption and integrity methods applied on communication with meters and customer premise equipment, through the protection of data resident in DWP databases, through the access control policies implemented for access and updates to data through web portals and the interface to external service providers to which customers may choose to grant access to specific usage data.

Privacy of customer data was addressed in the SGRDP deployment through the careful segregation of data within the system. Personally identifiable data regarding customers name, address, contact information and billing information is managed within the DWP corporate zone, where this data was resident prior to the creation of the smart grid demonstration project. Data used by smart grid applications, including location and usage data needed by the demand response functions are obtained through filtered interfaces (e.g. Interface 043) in which the personally identifiable information has been removed. Real time access to load data, when required by demand response, is similarly available in a de-identified manner.

Customers have access to their own data though the customer behavior portal, and access to this data is provided only after authentication of the individual as the party to which the data pertains. Authorization methods applied at the portal limit access to the customers own information. Administrative access to this data is available to DWP employees only.

The ability for customers to allow sharing of their PII, including usage information, has not been implemented, so compromise of customer data through that channel is not presently an issue. If shared third-party access to customer PII is allowed in the future, the utilities responsibility will be limited to allowing such access when authorized by the customer, but the utility cannot control what is done with the information once it is in the third-parties' hands.

Customer information is managed within the existing corporate systems of the LADWP, so integrity of customer information is ensured through existing methods in place at LADWP. Integrity of usage and other data generated at meters is maintained through cryptographic hash functions implementing digital signatures on the data as it flows through the AMI components and is placed in the Meter Data Management (MDM) system. The MDM system is present in the DWP Corporate Zone and protection of the integrity of the data once present in the MDM system is maintained through the existing IT protection mechanisms present at DWP.

Data Integrity and Availability

Integrity of system data is supported throughout the system by the use of encryption, check-sums, and digital signature technologies. The integrity requirements of data have been assessed for each category of data, and the appropriate integrity mechanisms applied. Where the integrity of data is required in transit only, a check-sum is calculated over the data before it is sent, and the data is communicated through an encrypted channel as part of the adopted communication protocol. In those cases where the provenance of the data must be maintained as the data moves from one component of the system to another, digital signatures are applied at the time of creation, for example, within the meters themselves.

As deployed, customer information is managed within the existing corporate systems of the LA DWP, so integrity of customer information is ensured through existing methods already in place. Integrity of usage and other data generated at meters is maintained through cryptographic hash functions implementing digital signatures on data as it flows through the AMI components and is placed in the MDM system. Once resident on the MDM system, integrity of the data is managed through restrictions on access to the MDM system.

Integrity of system components, including software, is monitored through a process that runs on each system and collects hashes of installed software components. Data is collected using AFICK and changes to programs in monitored locations are communicated to the CS zone where any new software components (including changes to components) are compared with authorized software in a white list, and changes that are not in conformance with policy result in a diagnosis event and an alert generated through the SIEM. Integrity of software and configuration updates to meters are further validated using digital signatures that are validated before new configurations or new software is loaded.

The requirement for real-time availability of devices and system data is supported through redundancy, both of communications channels, and of system components and data itself. Communicating from devices in the field is supported through cellular technologies and wireless mesh technologies. The mesh technologies enable the automatic generation of new communication paths relayed by devices until the communication reaches one of several Cisco Connected Grid Routers (CGR's) which provide redundant communication paths back to the utility. Meters configured for cellular communication are dependent on the carriers for redundancy in their communication paths. Communication with home gateway devices for the demand response capability is supported over the internet path, and redundancy is dependent on the Internet Service Provider (ISP) to which the customer subscribes. It is recommended that alternate communication paths through the AMI network plus the customer's internet connection, be supported for additional communication redundancy, but that redundant path has not been implemented.

Availability of data resident on the MDM system and at other storage components in the system is supported in some instances through live backups provided through the existing virtual machine interfaces for computers on which certain smart grid functions are implemented, as provided by DWP's IT group. Additional redundancy for the communication of certain data, e.g. meter reads, is supported through queued delivery – data that cannot be communicated initially remains queued and is delivered when communication is reestablished.

Security Logging and Monitoring

The data used for alarms, notifications, intrusion detection, and situation awareness originates in many parts of the system. Network monitors analyze network traffic looking for specific events, and disseminate information about such activities to Detection Diagnosis and Remediation (DDR) components as well as SIEM tools deployed as part of this project. Among the information collected is information regarding physical events in the system, such as changes in load at particular devices - e.g. meters, and changes beyond a configured delta, or meeting other configured characteristics is communicated into the SIEM for notification and visualization. This enables the detection of security events that occur beyond the control of LADWP, but which can affect the grid. For example, a coordinated compromise of a large number of electric vehicles through their cell phone control interface affects the observed load that must be matched through generation or load curtailment. While that attack might not occur on a part of the network that is managed or monitored by the utility, the effect of cycling of charging status can lead to generation of an event at the meter which is communicated to the SIEM infrastructure.

Within the deployed system we implemented two parallel components to detect attack signatures, identify anomalous behavior, and generate situational awareness information needed by the system. Existing commercial and open source intrusion detection aggregation components (part of the SIEM tools) were deployed. Additionally, we applied new data mining techniques to identify and classify routine or expected behaviors, so that the anomaly detectors learn expected behavior (even occasional expected behavior) and reduce the incidents of false positive alarms. Notifications of detected incidents or situations are made to operators and administrators, through the SIEM visualization interfaces in control centers based on policies that were developed as part of the security and safety assessment activities in the project.

Security Event Response

The design of the smart grid, and in turn, the SGRDP test bed, enables fast and appropriate response to security relevant events. What makes an event relevant from a security perspective is that the event directly impacts the required security properties of CIA, or that the event changes the probability of the

system to be able to maintain such attributes. Thus, an attack by an adversary constitutes a security relevant event, but so does the loss of lines, or communication resulting from natural events and acts of nature. Our approach to security for the SGRDP is both proactive and reactive.

On the proactive side, the architectural principals guiding the design provide for redundancy (in support of availability) and multiple trust domains with clearly defined boundaries that support strong isolation of critical data from users and processes that are in lesser trusted parts of the system (in support for confidentiality and integrity). Encryption and digital signatures are applied to protect data that is stored, or transmitted across parts of the system beyond the appropriate domain for which such access is required.

The project design also included capabilities on the reactive side, through intrusion detection and diagnostic capabilities. We developed a significant situational awareness component that is cognizant of the current operational state of the system and which models the likelihood of success of various attack techniques under the current (and projected) operational states. This capability can be used to advise on remediation measures that reduce the threat profile, even before an attack is able to successfully exploit a weakness.

The intrusion detection and diagnosis capabilities take into account physical characteristics of the system, and are useful in identifying faults (not just intrusions) within the system.

Software and System Updates

The system is able to adapt to evolving threats. This is accomplished through configuration of existing system components through regular updates to signatures and rule sets based on intelligence obtained external to the system, as well as changes to rule sets configured by system operators based on observed activity from the intrusion detection and situational awareness components of the system. In certain cases, additional defense components may need to be deployed within the system, and vulnerabilities in existing software will need to be corrected. These activities are possible through automatic software updates that may be propagated to various components in the system. Before updates are disseminated, the changes must go through a careful change management process. Updates are digitally signed using an encryption key that is maintained off the network, and validated by the device before an update is applied.

Change Management

Change management is a formal process used to ensure that changes to a product or system are introduced in a controlled and coordinated manner. It reduces the possibility that unnecessary changes will be introduced to a system without forethought, thereby introducing faults into the system or undoing changes made by other users of software. The goals of a change control procedure include minimal disruption to services, reduction in back-out activities, and cost-effective utilization of resources

involved in implementing change. Change management, also called Change and Release Management, in Information Technology Infrastructure Library (ITIL) terminology, is a critical process control. In audit parlance, change management provides the process and documentation that all changes to subject systems are authorized, approved for production, and do not adversely affect the appropriate controls, such as segregation of duties. North American Electric Reliability Corporation (NERC) and Federal Energy Regulatory Commission (FERC) standards devotes one complete Critical Infrastructure Protection (CIP) standard to Systems Security Management. This CIP alters impacted systems that protect both the security perimeter and the systems within the perimeter that are authorized, tested, and documented to assure the changes do not adversely affect existing cyber security controls.

Each demonstration entity must establish a plan to address change management. LADWP has a structured change management process that all LADWP network and application changes utilize. This provides documentation of new equipment that has a network connection, implementation and modification of applications associated with the SGRDP, and security implementations and modifications (access control changes, patches, etc.). The release management process for changes with a higher risk of introducing vulnerabilities (e.g. new web facing applications) is reviewed to limit the introduction of new security issues.

Because the Demand Response extends into "uncontrolled" domains, such as private residences, the change management regimen is only able to extend to the institutional perimeters.

Change management within the SGRDP is closely tied to the system integrity component described in section 2.3. In particular, only authorized changes to hardware and software components are added to the policy component in the integrity monitor, and are white listed. Changes to system components not in conformances with this policy are detected, and the diagnosis of an unauthorized software component is communicated to the SIEM for visualization, altering, and operator action.

Cyber Resilience

The Smart Grid exposes the U.S. electrical infrastructure to two-way IP communications and the execution of control commands, which in turn raises a number of very serious risks, some of which are:

- The increased probability of serious attacks on entire transmission and distribution systems from remote locations.
- Unauthorized access to the entire grid through poorly protected customer computers.
- A weakening of the security posture of transmission and distribution systems.

These risks highlight the importance of cyber resilience – the ability to operate the grid through attack and failure, and its obvious impact on grid viability. At the core of the SGRDP cyber security approach is

a concerted effort to address cyber resilience. To have such resilience means that the SGRDP must have some capacity to actively defend itself against increasingly sophisticated and agile cyber threats, as well as be able to recover quickly from cyber incidents—whether they are caused by malicious activity, accident, or natural disaster. Experience has shown that such cyber resilience requires a coordinated approach across a number of areas that include preventive security (i.e., hardening the underlying infrastructure to be more resistant to penetration and disruption), active response, policy and compliance, risk assessments, security operations and so forth.

The cyber-security deployment for the SGRDP includes an in-depth treatment of detection, diagnosis and remediation technologies to promote resilience to cyber-attacks and faults. It applies well-seasoned detection, diagnostic and remediation technologies from JPL and USC-ISI to this end. Furthermore, the security components leverage the extensive test expertise at JPL and the sophisticated test infrastructure at USC-ISI (USC's DETER test bed) to provide a rigorous modeling and test regiment assuring that the detection, diagnosis and remediation technologies produced are effective in a larger scale smart grid environment.

Testing

A central issue in cyber security today lies in the area of testing. Testing the operational efficacy of a given technology to show, unambiguously, the degree to which that technology will improve the cyber resiliency of the system (smart grid) as a whole is a difficult task. This problem is made more difficult for cyber-physical systems, such as the smart grid, when the physical system responses may create additional control and information channels that might not be readily apparent to purely cyber-emulation and simulation tools.

The goal of our test effort was to provide assurance that the system under test will perform "effectively" in a wider range of situations than might be present in the early stages of operation. Since the operational environment is subject to a significant amount of variation (consider for example the complex, non-deterministic behaviors often observed in highly networked environments) and unpredictability (as is sometimes the case with adversarial activity), then it becomes a challenge to design test regimes that will effectively exercise a system under test through the variations and unpredictable behaviors that it will face over time.

In deference to both the complexities of the cyber environment and the inherent sophistication of many cyber security technologies, our testing approach focused on two main areas:

- Testing regimes and metrics – this recognizes the importance of designing rigorous test regimes and effective metrics for producing robust results that describe immutable performance properties of the system under test.
- A comprehensive test framework – the test process to thoroughly evaluate the effectiveness of the cyber security measures/technologies that includes regression testing throughout the operational lifetime of the technology, while accounting for not only hypothetical cyber-threat scenarios, but also various scenarios of physical system -state (lines down, load profiles). This

framework accounts for responses to change in extrinsic physical system state, as well as changes in physical system state caused by cyber state and inputs to the system.

These goals were met through the use of a combination of modeling and simulations to understand system response to attacks on a scale larger than was deployed in the SGRDP, in combination with component testing of the security components deployed within the SGRDP, and through the injection of generated (simulated) attacks into the monitored event streams, allowing us to verify the intended response to stimuli that were not practically implemented in practice (e.g. we were not willing to shut down large numbers of customers for testing, yet we were able to determine the response of the detection, diagnostic, and remediation components to such simulated events).

Summary of Cyber-Security Risks and Mitigation Strategies

Although traditional IT systems have been, and continue to be, subject to cyber-security risks in all forms, the implementation of a fully interconnected Smart Grid brings with it a special set of cyber-security risks that have been identified by many in the Smart Grid community. A summary of these grid-pertinent cyber-security risks are as follows:

- Greater complexity increases exposure to potential attackers and unintentional errors;
- Networks that link more frequently to other networks introduce common vulnerabilities that may now span multiple Smart Grid domains (see Figure 2) and increase the potential for cascading failures;
- More interconnections present increased opportunities for “denial of service” attacks, introduction of malicious code (in software/firmware) or compromised hardware, and related types of attacks and intrusions;
- As the number of network nodes increases, the number of entry points and paths that potential adversaries might exploit also increases; and
- Extensive data gathering and two-way information flows may broaden the potential for compromises of data confidentiality and breaches of customer privacy, and compromises of personal data and intrusions of customer privacy.

For the SGRDP, the cyber security strategy is concerned with mitigating these risks including those risks presented by new cyber security threats and vulnerabilities in a way that protects the SGRDP against broad-based systemic failures. Consequently, the SGRDP cyber security approach is a tight integration of 2 main areas:

Integrated risk management process

The most important component in mitigating the summary of risks laid out above is the risk management and assessment process that the SGRDP infuses at each stage of the project lifecycle. The threat landscape is consistently moving, new threats and vulnerabilities will occur. The risk assessment cycle is a vehicle that constitutes a disciplined and methodical approach to identifying and mitigating new threats.

Defense-in-depth

Because cyber security threats are diverse and evolving, the cyber security architecture for the SGRDP is best described as an implementation of a "defense-in-depth" strategy where prevention, detection, response, and recovery are critical facets. Multiple levels of security are implemented, thus should one component of defense be circumvented, the several other layers of security will serve to mitigate the risk to other components of the system. In previous sections we have already introduced and described a number of these security controls that will be implemented for the SGRDP to form its defense-in-depth approach, for example, cyber resilience, data confidentiality, privacy and trust.

Risk Assessment Process

Since the Smart Grid includes systems from the IT, telecommunications, and electric sectors, the risk assessment process was applied to all three sectors as they interact in the Smart Grid. The SGRDP risk assessment was largely patterned on the National Institute of Standards and Technology Special Publication (NIST SP) 800-30 methodology, incorporating the Federal Information Processing Standard (FIPS) 200, "Minimum Security Requirements for Federal Information and Information Systems", and FIPS 199, "Standards for Security Categorization of Federal Information and Information Systems" where the levels of impact are defined. In addition, the SGRDP risk assessment process assimilates the pertinent elements of the assessment process as described in the National Institute of Standards and Technology Interagency Report (NISTIR) 7628 Volume 2 that is specific to the Smart Grid.

The subsequent sections will provide the details, considerations and enhancements that the SGRDP risk assessment process applied over the basic process described in the NIST SP 800-30.

Initial High-Level Risk Assessment for SGRDP

Traditionally, risks to cyber security fall into three classes – compromise of confidentiality, compromise of integrity, and compromise of availability – which, for the purpose of this assessment, we equate with resiliency. To assess the risks to the SGRDP's mission, the implications of compromise of each of these characteristics to each element of the smart grid were assessed, and the approaches for mitigation are described. In making this assessment, we considered the following elements of the smart grid: the AMI, electric vehicles and their charging infrastructure, demand response, customer behavior, and cyber security. In addition, we discuss the impact of customer and the impact to the utilities pre-existing operational systems.

AMI

The function of the AMI component of the system is to provide data on usage and status (including diagnostic information) to the utility, and to support limited commands to the meter from the utility. The communications provided through the AMI may provide a path for communication through the meter to and from equipment on the customer premises, although as deployed it is only used for communication with the meter itself. The integrity and confidentiality of all data and commands transmitted through the AMI are critical.

Through this section we correlate these scenarios with the use cases defined by the National Electric Sector Cybersecurity Organization Resource (NESCOR) is also described. The NESCOR use cases can be found at: http://smartgrid.epri.com/Repository/Repository.aspx

The following lists key AMI threats:

AMI.T1. Compromise of integrity of usage data can result in theft of power, through incorrect billing.

AMI.T2. Compromise of integrity of current status can result in the utility configuring their generation or distribution based on faulty information.

AMI.T3. Compromise of confidentiality of status or usage data will violate users privacy and potentially allows an adversary to learn a customer's routine (e.g. when they leave in the morning, return at night and if they are on vacation).

AMI.T4. Failure of an operating meter may result in loss of power to the circuit behind the meter, or failure to measure load resulting in faulty billing.

AMI.T5. Failure of the communications channels could occur for several reasons, including overconsumption of resources, possibly intentional due to a denial of services attack, or by radio jamming, unintentional interference, and failure of intermediate relay nodes, or through intentional cutting of cables.

AMI.T6. Failure to communicate (loss of network resiliency) for an extended period could potentially result in loss of billing data, preventing proper billing for the resources consumed.

AMI.T7. Failure to communicate (loss of network resilience) in the short term could prevent visibility of power load and other conditions.

AMI.S10 (labeled "S" for Safety). Acceptance of a forged command to turn power back on at a residence could result in the energizing of a circuit with a fault, or that is not otherwise ready to accept power, creating an electrocution or fire hazard.

As deployed, protection against threats AMI.T1-T3 and AMI.S10 is provided through use of cryptography. Meters are provisioned with individual keys that are used to digitally sign the data that is communicated upstream. Individually exchanged keys are used to encrypt the data that is transmitted as well, providing assurance that such data cannot be read by unintended receivers, including by other meters sharing the communications medium. For the meters communicating through mesh networks, intermediate nodes relay opaque data that cannot be interpreted by these intermediate nodes.

As deployed, protection against threat AMI.T4 is supported by self-tests when the meter restarts. Failure of a meter to communicate for an extended period of time, results in dispatch of repair personnel to the site, where they can investigate the cause of the failure.

We planned to partially protect against threat AMI.T5 through the use of redundant communication channels, when available. At present meters only support a single direct communications technology through the AMI, deployed for some meters through a mesh network, and for others through commercial wireless data network (cell cards). Meters may also be connected to a home area network, and we intended for that to provide a backup channel for communication to the utility. That functionality was not implemented. Because all communication is protected for confidentiality and integrity as describe above, this secondary channel could become usable to improve reliability of the communication.

Mitigation for threat AMI.T6 is managed because meters have sufficiently large buffers to store several months of usage data, pending an authenticated acknowledgement of receipt of the data by the data collection components of the AMI. Additionally, the meters have sufficient registers to hold all necessary unique rate periods for a similar interval and will send register data in addition to (or instead) of interval data. This ensures that even if interval data is lost, one can reconstruct that amount to be charged from the register data.

While certain failures of type AMI.T7 can be prevented through the use of redundant channels described in addressing AMI.T5, that redundant channels was not implemented, and it is inevitable that there will on occasion be loss of communication with meters. This threat is mitigated by requiring acknowledgements by the meter for execution of commands, with manual overrides and fail-safe operational behaviors (this latter strategy is important for threat S10 as well). These mitigation

strategies are more specific to the power domain than to security. The distribution system and all other components of the smart grid were designed so that failure to communicate with individual meters results solely in degraded operation, cannot lead to failure of the smart grid as a whole, and does not result in loss of safety in any part of the system.

Demand Response (DR)

The function of the DR component of the system enables variation of the load placed on the smart grid based on the receipt of data regarding system load and power availability. This data can take the form of pricing signals or load curtailment requests. As deployed, only load curtailment requests have been implemented. The DR component is hierarchical, in that signals received from the utility form the basis upon which derived signals are communicated to other components of the DR system. These signals may be obtained and relayed through a meter and the AMI, but as deployed they may communicate over the internet using OpenADR.

The following lists key DR threats:

DR.T1. Compromise of integrity of pricing signals and or load curtailment request can lead to unnecessary equipment shutdowns, undesired increase in consumption, or over use during expensive pricing periods.

DR.T2. Compromise of integrity of current status or of responses to load curtailment request can result in the utility configuring their generation or distribution based on faulty information.

DR.T3. Compromise of confidentiality of status will violate customer's privacy or allows an adversary to learn about a customer's shutdown of operations.

DR.T4. Failure of a DR component may prevent the utility from meeting a need to reduce load requiring more invasive responses including rolling blackouts, or in some cases failure of the grid as a whole.

DR.T5. Failure of the communications channels could occur for several reasons, including overconsumption of resources, possibly intentional due to a denial of services attack, or by radio jamming, unintentional interference, and failure of intermediate relay nodes, or through intentional cutting of cables.

DR.T6. Failure to communicate (loss of network resiliency) will prevent the DR component from receiving load curtailment signals, preventing the required response, and may prevent the utility from meeting a need to reduce load requiring more invasive responses including rolling blackouts, or in some cases failure of the grid as a whole. Failure to receive a pricing signal, or failure to respond to a load curtailment request could result in higher charges for the customer.

We protect against threats DR.T1-T3 through use of cryptography. DR components are provisioned with individual keys that are used to digitally sign the origin of data that is communicated upstream. Individually exchanged keys are used to encrypt the data that is transmitted as well, such as load curtailment signals and status responses, providing assurance that such data cannot be read by unintended receivers.

We protect against threat DR.T4 through the application of system integrity mechanisms that are part of the configuration management components described earlier. Additionally intrusion detection technologies will be deployed on the system, and behavior is monitored to assess the security health of the components.

We planned to partially protect against threat DR.T5 through the use of redundant communication channels, when available. These channels were not implemented, but would augment the internet channel with communication through the AMI and meters into the home area network. Because the AMI network is dedicated to particular functions, it may be available when the rest of the internet is subject to denial of service (or simply over-consumption of resources, or failure caused by an unreliable internet service provider -- the most likely cause).

While certain failures of type DR.T6 could be prevented through the use of redundant channels described in addressing DR.T5, it is inevitable that there will on occasion be loss of communication with DR components. This threat is mitigated by requiring acknowledgements by the DR component for the execution of commands. The mitigation strategies are more specific to the power domain than to security. The distribution system and all other components of the smart grid have been designed so that failure to communicate with enrolled DR components results solely in degraded operation, cannot lead to failure of the smart grid as a whole, and will not result in loss of safety in any part of the system.

Electric Vehicles (EV)

As deployment is planned in the SGRDP, the electric vehicle component provides functionality that has already been described in both the AMI and the demand response projects. The threats described for those components, and the reduction and mitigation strategies, are included by reference.

The following lists key EV threats:

EV.S8. Excessive and rapid charge/discharge cycles for the electric vehicle battery can reduce its life, as well as cause a safety hazard.

EV.S9. Failure to charge an EV due to unavailability of communication with the smart grid infrastructure will leave the vehicle without sufficient charge for emergency use. Similarly, the discharge of the vehicle to feed power into the grid will leave the vehicle without sufficient charge for emergency use.

EV.S10. Plans call for use of the EV batteries to feed power into the grid. If segments of the grid are energized unexpectedly, this can cause a safety issue for workers.

Threats EV.S8 and EV.S9 are partially addressed by providing integrity to commands, as describe for AMI and DR, but that only protects against malicious attempts to affect the charging or discharging of the vehicle. EV.S8-S10 also requires local control, through the use of governors and other logic in the charger that ensures that charge and discharge rates do not exceed safe levels. These techniques may utilize temperature sensors in the vehicle charging system. Such logic may also set a minimum level of charge that will be maintained whenever the vehicle is connected, as long as the vehicle can be charged safely.

Customer Behavior (CB)

The customer behavior component of the SGRDP is the only part of the system that has access to customer-sensitive information (except for the AMI component, which generates such data, feeds it to the utility, but never retrieves such information). The customer behavior component of the project is not involved in the operation of the smart grid. As such, the threats to the CB component focus on this data, and in particular on its integrity and confidentiality.

The following lists key CB threats:

CB.T1. Compromise of integrity of usage data as presented to the customer can result in unexpected behavior by the customer, affecting consumption, as well as a loss of satisfaction by the customer.

CB.T2. Compromise of confidentiality of personally identifiable information, or status or usage data will violate users privacy and potentially allows an adversary to learn a customer's routine (e.g. when they leave in the morning, return at night and if they are on vacation).

CB.T3. Impersonation of a user (due to a lost password), or incorrect policies applied to control access to usage and personally identifiable information will result in compromise of privacy of the affected party.

Threats CB.T1 and CB.T2 are addressed through the application of cryptography on the channel between the user interface (whether a dedicated device, or between a web browser and a web server) and the data repository where such information is stored. This is implemented using the TLS protocol on such connections.

Thread CB.T3 is partially addressed by careful creation of the policies that are enforced through the customer usage database, and through the use of strong identity management techniques and intrusion detection components to identify misuse of login credentials. Additionally, personally identifiable information regarding the customer is stored in the DWP corporate zone where existing privacy and confidentiality policies are already in place. Customer identity management is supported through interfaces previously implemented for DWP's customer portal.

Impact of SGRDP on the Department of Water and Power Operational System

Interfaces between the SGRDP and the LADWP operational system lie in two areas: (1) the power consumed and managed within the SGRDP comes from the LADWP, and thus there is a "physical" interface between the two systems, and (2) meter data from the AMI components of the SGRDP are fed into LADWP's meter data management (MDM) system, an operational system that manages data from other customers as well.

The following lists key Operational System threats:

DWP.T1. Instability of the load within the demonstration project will impact the proper operation of the remainder of the LADWP grid.

DWP.T2. Interface between the smart grid demonstration and the LADWP meter data management system could be used to access customer data that has not been authorized by customers.

Threat DWP.T1 is related to the physical system and must be addressed by LADWP engineers, likely through the use of governors and other limits on the power interconnection between the demonstration and the rest of the grid. As deployed, the scale of the SGRDP is not large enough to create significant instability to the larger LADWP grid. As part of the modeling activities of this project, we studied the potential impact of larger scale changes to the load profile that would be present from a full deployment of this technology and identified thresholds at which such instability would be observed.

Mitigations of DWP.T2 were addressed by prohibiting the flow of data from the LADWP system into the demonstration. This was accomplished in part through the application proxy provided by the DataPower appliance, and also through the creation of “Interface 043” which creates a shadow database within the demonstration to hold copies of the usage data from those customers in the demonstration that have authorized its access through the demonstration web portal.

External Impact on the Smart Grid Demonstration Project (SGRDP)

The Home Area Network (HAN) and many loads within the customer premises include devices that are not under the utility's control, some of which are accessible through the open internet and even smart phone interfaces. These devices must be treated by the SGRDP as suspect. The interactions of these devices create threats to the smart grid.

The following lists key external threats:

Ext.T1. Communication from customer-owned devices and network can mount denial of service attacks, or penetration attacks against the smart grid infrastructure.

Ext.T2. Changes in the power consumed by external customer-owned devices creates a physical control channel into the smart grid, and can impact the stability of the system.

Threat Ext.T1 is mitigated by disallowing direct communication into the utilities network (i.e. the AMI network) from untrusted devices on or beyond the HAN. These devices are allowed to communicate with controlled interfaces on the HAN "gateway" and through the open internet using OpenADR. The HAN gateway, does not relay packets as presently deployed, but may accept status updates, and relay the data in the status updates to the utilities.

Threat Ext.T2 is a physical threat, and must be mitigated through procedures within the management of power on the smart grid that governs regions of the network, disconnecting them if loads change in such a way that will destabilize the rest of the grid. The detection, diagnosis, and remediation components of the SGRDP were designed to detect correlated changes in load profiles that might indicate the presence of such an attack. As deployed, mitigation takes the form of an alert to such detected correlated activity and human response is necessary to implement any corrective action. The current scale of the SGRDP prevents these changes from affecting the operational resilience of the larger grid, but a larger scale deployment would violate this assumption.

Cyber Security (CS)

The cyber security component of the SGRDP is responsible for supporting security throughout all of the other components of the demonstration. The key management component supports the confidentiality and integrity techniques discussed in each of the other threat sections. Similarly the identity management and policy components support access controls throughout the entire system. Finally, the intrusion detection and situational awareness components enable reporting of security relevant events to operators, and response that is affected through changes to the policies managed by the policy module. The ID component requires input of data that originates throughout the system.

The following lists key cyber security component threats:

CS.T1. Compromise of the key material from the key management module, or credentials from identity management would leave the entire system vulnerable to breaches of confidentiality and integrity.

CS.T2. Compromise of the policy database could enable access or control functions to be performed by individuals not authorized for such operations.

CS.T3. Failures of communication could prevent proper provisioning of keys, or validation of access policies.

CS.T4. Failures of communication could prevent communication of security incident and event data crucial to the proper function of the intrusion detection and situational awareness components.

We address threats CS.T1 and CS.T2 in the design of the key management and policy infrastructure as deployed in the individual component of the SGRDP.

Managing the lifetimes of keying material and credentials will mitigate Threat CS.T3. The components for which any central key management infrastructure is responsible pertains to persistent keys provisioned when an AMI device is deployed, and updated periodically, but not on each use. Session keys are generated from the longer term credentials using methods that require only communication between the communicating endpoints, a channel that must be available anyway for communication to occur.

Threat CS.T4 results in degraded operation of the intrusion detection and situational awareness component. Periodic status (keep-alive) updates are used to enable the system to identify such communication failures, and generate an alarm when certain thresholds are reached.

Defense-in-Depth

The SGRDP defense-in-depth approach incorporates both standard security mechanisms as well as the results from a research and development effort into the next-generation cyber security technologies that will serve to protect full-scale Smart Grid deployments against external threats, internal customer behaviors, and unanticipated design issues without risk of damage to actual deployed systems.

The application of standard security mechanisms provides the SGRDP with a basic security foundation, one that can be incorporated into any Smart Grid deployment. In essence, we designed the SGRDP system to incorporate tried and tested security approaches such as AES-256 encryption for confidentiality, message authentication & message digests / hashes for integrity, and various measures to ensure authenticity such as Public Key Infrastructure (PKI) authentication.

SGRDP's New Approaches to Security

Unique to the SGRDP is the effort to research and develop new technologies and approaches that aim to advance the state-of-the-art in cyber-defense for the Smart Grid.

Our efforts in this area were to establish new paradigms and approaches to address those risks that arise when preventive measures such as firewalls, encryption, and other standard security measures fail,

i.e., when the SGRDP system fails to meet its mission objectives due to the manifestation of risks such as unanticipated failure, zero-day attacks, misbehaving insiders, and problems of similar ilk.

Three significant areas comprised our efforts in this regard:

The first most directly impacts the issue of active resiliency for the Smart Grid – namely the provision of effective detection and, diagnostic and remediation strategies against cyber-attacks.

The second lies in the design of the SGRDP system with fault containment regions that provide the capability to either a) contain the consequence of an attack or the attack itself, and b) to isolate those highly critical regions that must continue to provide mission critical operations in the presence of failures. The containment capabilities for the SGRDP were deployed through a series of defense methods described in much more detail in the second part of this report (**forward citation**).

The third significant area of study was to provide effective testing regimes to validate that our solutions conferred resilience to cyber-based attacks and failures to the SGRDP system and to show that various aspects of those solutions can be applied to the general Smart Grid outside the purview of this demonstration.

Detection and Diagnosis

Detection and diagnosis lie at the heart of active resilience to attacks/faults as well as at the heart of the DOE's "Smart Grid Cyber Mission" (https://www.arrasmartgridcyber.net/index.php). It is necessary to know that there is a problem (detection), be able to accurately find out what caused that problem (diagnosis) and then design a strategy to address that problem effectively (remediation).

Detection

While there have been numerous efforts to provide intrusion detection systems to detect attacks, prior technologies were plagued with significant shortcomings, including high false alarms and miss rates. Furthermore, their capabilities with regard to the effective detection of zero-day attacks remained questionable. One prominent factor contributing to these problems lies in the deployment of detection algorithms without a good characterization of both the algorithm and the environment into which the detection algorithm is deployed, i.e., a clear quantification or measure of background noise and attack signal how the two affect the accuracy of a given detection algorithm.

We addressed these problems by designing a detection capability tailored to the general Smart Grid environment but first deployed on the LADWP SGRDP system. We used well-characterized detection algorithms from USC-ISI and JPL's core complement of detectors.

Diagnosis

It is well known that false positives are a common problem in intrusion warning/detection systems. These false positives can lead to dangerous and sometimes catastrophic consequences if acted upon without verification. Diagnostic technologies (tools and systems) aim to provide the necessary evidence to support assertions that an attack or fault actually occurred

While numerous efforts have focused on detection of intrusions and cyber-attacks, there has been a noted absence of detailed studies into principled diagnostic approaches that inform on the impact of an attack on the underlying cyber-physical infrastructure such as the electric grid. A rigorous diagnostic capability is particularly critical in the recovery process, as an effective remediation strategy can only be designed when guided by an accurate diagnosis of how an attack has affected critical components and functions.

We addressed this limitation by employing state-of-the-art model-based techniques for understanding the impact of an attack and plan to use those models to assess candidate recovery actions.

At the core of our approach is:

A diagnostic and remediation capability for cyber-physical systems based on an evidentiary and reasoning process that integrates both the cyber infrastructure and the physical environment.

A focus on accuracy and a study of how uncertainty affects the quality of diagnostic results.

The capability to leverage the results from existing detection algorithms in both the cyber and the physical domains as evidence in an assessment of how detection results can contribute to the diagnostic context.

Fault Containment Regions

Detection and diagnosis of a compromised system make up only half of the equation to reducing the potential impact of a fault or attack. If allowed to persist or propagate through the system unfettered, faults and malicious attacks can have a catastrophic impact to the core functions of the system. The system must therefore also have a means of containing or correcting the problem in a timely manner to effectively reduce its impact while maintaining core functions of the system.

Along with the above functions, the following functions and design principles were applied to the SGDRP to ensure that the system effectively address a compromised function or system:

Passive fault containment: Control the physical and functional interfaces between systems such that incorrect behavior of one system cannot impact the function of a connected system or higher function.

This was addressed through the application of fault containment regions and protection domains described earlier.

Active fault containment: As part of the response to a detected failure or attack, take steps to contain the failure effects to the affected system such that connected systems or higher functions are not impacted.

This was addressed through the application of a policy module to authorize load curtailment or remote disconnect in order to ensure the system remains in a resilient state.

Fault recovery: Where necessary, the system should be capable of restoring critical functions by correcting the diagnosed fault or switching redundant systems into use in place of a failed system.

At present, this is provided through alerts to operators of unsafe states and recommended remediation actions. We are not prepared at this time to allow the system to initiate response without operator intervention.

Testing Methodology

Testing regimes were deployed to validate that the Smart Grid is indeed resilient to cyber-based attacks and failures given the incorporation of various technologies and their corresponding claims of efficacy.

To be effective requires accurately modeling the operational environment within a testbed environment (operational environments are typically complex and riddled with non-deterministic behavior that are difficult to isolate),

Understanding the interactions among the testbed components that may inject errors into the test regime and consequently undermine the quality of the results,

Understanding the causal inferences that may contribute to experimental confounds – a phenomenon that will also undermine the quality and veracity of the results.

Higher system level modeling was based on industry power models as guided by the deployed topology for the SGRDP. Further data from the operations phase of the SGRDP is needed to refine these models to situations specific to the SGRDP.

Summary of Risk Assessment

The purpose of the security component of the SGRDP was to provide protection for SGRDP deployed components including the advanced metering infrastructure, demand response, electric vehicle components and customer behavior functions across the infrastructure, i.e. for components deployed in systems under the physical control of the LA Department of Water and Power, components in the field, and also components on customer premises. These components of the system were to be protected against denial of service attacks, traditional cyber security penetration, subversion and malicious code, and new forms of cyber-physical attacks.

These protections have been provided as described in this report through careful attention to the SGRDP architecture and the deployment of certain technologies to enforce architectural isolation of the system.

These design methodology and technologies included:

- The deployment of the SGRDP in carefully defined fault containment regions.
- Multiple deployed isolation mechanisms described in part two of this report)
- Cryptographic techniques for integrity and confidentiality applied through the communications protocols used for demand response, AMI, customer behavior, and security functions of the system.
- Advanced Detection, Diagnosis and Remediation technologies that act upon and correlate data from both the cyber domain and physical domains to detect attacks and failures and understand the impact of a failure on the operational resilience of the system.
- A policy engine that applies system stability and safety models to authorize load curtailment and remote connect/disconnect, as well as candidate remediation activities. At present, this engine monitors actions and generates an alert if these functions will not maintain safe operational states.
- System integrity capabilities to validate system changes before installation on hardware in the field, and to identify unauthorized system software and configuration changes to all elements in the SGRDP.
- Extensive simulation of the system impact of cyber and physical compromise, with these models used by the diagnosis component and eventually for use in assessing candidate remediation activities.

The security approach of the SGRDP deployment also applies and leverages the classic cyber security solutions already in place at the LA Department of Water and Power. Among the classic cyber security components were the technologies supporting containment, which are described and evaluated in the next section of this report.

Technologies Deployed

DWP Firewall

Capability required in SGRDP Design

This firewall determines whether communication from the internet to DWP systems conforms to policy, blocks packets that are not conformant, and routes packets that are authorized. This firewall is maintained by DWP and is not a smart grid demonstration component, although data from users, home area networks, and external providers does cross this system.

Because of the amount of traffic passing through this device (or devices), performance and support are critical. As a result this firewall should be a commercially available and supported product. With respect to the capabilities required for a sculled smart grid, the special requirements include:

1) the ability to dynamically cut off / block specific flows when instructed remotely by DWP management interfaces
2) The ability to communicate detailed audit records for blocked flows to the SGRDP DDR components.

This second requirement is important if the DDR component is to have visibility to attacks that are blocked by this enterprise firewall, and this was not a capability that was available during the demonstration deployment. Because the majority (though certainly not all) of attacks on a smart grid are easily blocked, this prevented our team from identifying the most prevalent attacks on the system, leaving only the attacks that made it through this first line of defense to be analyzed.

Because analysis of the data and operation of the DDR component in the demonstration was to be performed by individuals that were not employees of DWP, access to this information would include access to DWP, but non-smart grid traffic, and would be counter to policy. This can be addressed in a scaled deployment in several ways:

a) Audit records on blocked flows is presently sent to the DWP SIEM component, and plans are in place for a filtered view of that data to be communicated to a secondary SIEM within the SmartGrid zone. From there, the data could be read by SmartGrid specific DDR components and used to detect, diagnose, and remediate intrusions.
b) High end commercially available firewalls support a monitoring port through which copies of all traffic is sent. Additional monitoring hardware on this port can perform more detailed inspection of packets and send summary information and detected attacks destined for the SmartGrid zone to the Smart Grid DDR components, in addition to recording all detected attacks to the enterprise SIEM.

Technological capability meeting those requirements

Commercial off the shelf technology is available to meet the requirements for the DWP Enterprise firewall and should be used. The specific additional requirements described above can be implemented in separate monitoring components connected to the firewall, or through configuration of DWP's enterprise SIEM in multiple levels.

Scalability of the capability

Scalability issues with this configuration are related to the throughput and reliability of the enterprise firewall, and commercial products are sufficient to meet this requirement.

Recommendations for how that capability should be met in a full DWP deployment

This capability should be met through deployment of commercially available high performance firewall components, with monitoring capabilities managed through a commercial SIEM, with possible additional monitoring components connected through a monitoring tap supported by the commercially available firewall.

VLAN Containment

Capability required in SGRDP Design

The SGRDP design requires that communication across zones must be mediate and controlled by a firewall component that will monitor the flows and allow only flows between pairs of hosts that are cataloged in the network flow table (appendix A) and network flow diagram (above). While this may be accomplished by using separate physical interconnections for each zone, flexibility in deployment and management of these zones can be accomplished through Virtual Lan containment where the same physical infrastructure is used, bit virtual separation is provided to allow direct communication only between nodes on a common virtual LAN.

Technological capability meeting those requirements

During the demonstration, separation between the SGRDP zones was provided through virtual LAN technologies, to enable rapid reconfiguration of zones.

Scalability of the capability

As discussed earlier, the 11 fault containment regions in the design were reduced to 4 zones (plus the internet and customer premises). This was done to ease management of the network and reduce the number of required gateway interfaces. That was done at the expense of our ability to manage in mediate flows between devices in the same network zone. In a scaled operational deployment, options need to be assessed regarding the use of VLANs for containment, vs physical separation of zones, and also to the usefulness of implementing separate zones for each of the fault containment regions. Control of flows between fault containment regions sharing a common VLAN (zone) can be accomplished through the use of distributed host based firewalls.

Recommendations for how that capability should be met in a full DWP deployment

The tradeoff between physical separation vs VLAN containment needs to be carefully considered. Physical separation will complicate the reconfiguration / movement of machines from one security zone to another, but that was required primarily during the demonstration deployment as we learned where

best to place components for performance and to work around delays in deployment of other components. A scaled operational deployment should have fixed placement of servers in zones, so physical separation is recommended.

Datapower Device

Capability required in SGRDP Design

The DataPower application firewall proxy manages the flow of sensitive information out of the DWP corporate zone, and from the AMI component to other SGRDP zones. An application proxy is necessary because the data flowing between domains must be assessed according to its content. Some data between a common pair of endpoints is authorized, whereas other data may not make the transition into the smart grid application components.

Technological capability meeting those requirements

The IBM DataPower appliances are used and have been programed to perform the necessary mediation of data flows at the application layer.

Scalability of the capability

Application firewalls such as the Datapower are necessarily lower throughput containment technologies than network layer firewall appliances. As a result, in a scaled deployment of the SmartGrid to all DWP customers, the DataPower appliances will need to be replicated, and the flows spread across multiple devices.

Recommendations for how that capability should be met in a full DWP deployment

In the alternative, it is likely that a full scale deployment of the smart grid will result in the operation of many of the SmartGrid application systems (e.g. Demand Response) to be transitioned to DWP control (as compared with the joint management with university partners during the demonstration). This change in the level of vetting of the staff, and in the operational security applied to the application servers, may allow an easing of the containment requirements applied to some of the information (expanding the DWP corporate zone boundary). That may eliminate the need for the DataPower device and enable use of the other technologies for containment (network firewalls and VLAN or physical containment) instead.

CS Firewall

Capability required in SGRDP Design

The CS firewall was deployed to mediate and monitor traffic between the internet and the DDR and Security zones within the smart grid demonstration project. For the demonstration this capability was implemented in software (as extensions to Linux) on rack mounted hardware dedicated to filling this firewall and router function. The CS firewall monitored communication flowing between zones connected to the firewall and communicated detected events to the detection, diagnosis, and

remediation engines in the security zone. It monitored entries in the DDR database looking for directives from the remediation components that change policy to block or rate limit specific flows. The capability was demonstrated in June of 2014 as shown in the demonstration scenarios [Cyber Security CS Document DDR March 2014 Delivery Description version 1.4, June 5, 2014; and Cyber Security CS Document DDR August 2014 Integration of SGRDP Detection and Diagnosis – Basic, Version 1.2, August 21, 2014]. While the technology was successfully demonstrated, the software implementation on top of Linux created management issues – in particular, the need to upgrade a custom Linux implementation to incorporate new patches.

The CS Firewall (detection, autonomic diagnosis, and remediation) is a system running a Linux based firewall router that connects outside communications to the SGRDP zones, and which supports transit across zones within the SGRDP (except for those transitions using the application Proxy Data Power Devices). This firewall has been modified to collect additional event data based on pattern matches and based on network flow statistics. The CS Firewall also monitors its own heath (with the same capabilities as provided for other machines within the SGRDP) and reports back to the CS Database with data regarding data bandwidth, traffic patterns matching configured filters, and host health statistics. The CS firewall is capable of making diagnosis based on locally collected data (autonomic diagnosis). Such diagnoses are based on rules loaded to the firewall in advance. The CS firewall can take atomic remediation actions based on such diagnoses. In the normal case, the CS firewall also monitors relevant data added to the CS database by the separately located diagnosis engine and takes remediative action based on those rules.

Technological capability meeting those requirements

The capability was demonstrated in June of 2014. While the technology was successfully demonstrated, the software implementation on top of Linux created management issues – in particular, the need to upgrade a custom Linux implementation to incorporate new patches. Because of the maintenance burden associated with operations of a customized software implementation, the CS firewall was subsequently configured out of the network configuration, and replaced with the DWP maintained firewalls discussed in sections A and B, which lacked the rate limitation and DDR integrations from the original design.

Per the original plan, development of advanced capability for diagnosis and remediation was ongoing based on data observed in the operating phase of the SGRDP. A simple diagnosis and remediation components was developed for and demonstrated in the Basic DDR demonstration in June 2014. That component monitors the CS Database for records from the CS firewall matching 1) a particular attack signature, and 2) excessive communication between pairs of components indicative of a denial of service attack. Upon detection, these components record the diagnosis in the CS database and generate remediation activities to 1) block packets from the host that triggered the attack signature detection, and in case two, the remediation action added to the database that instructs the CS firewall to impose rate limitation on the communication between the offending pair of communicating end-points. These actions are read from the CS database by the CS firewall which enforces the remediation action.

Descriptions of the methodologies and algorithms utilized

The Basic DDR delivery demonstrated the capabilities of the collection framework to collect data, for the diagnosis engine to perform very basic analysis of the data to detect relevant and actionable events, and to show how remediation activities are communicated to the policy enforcement points throughout the system. An advanced DDR capability is under development (per the original plan, this capability is constructed based on the data that is now being collected within the SGRDP). The methods for collecting, diagnosis, and remediation based on the data have been described in section 3, above, for each of the CS components participating in the data collection.

Scalability of the capability

For scalable deployment of this technology to a DWP wide deployment, the capability that was successfully demonstrated needs to be incorporated by vendors into off the shelf appliances for deployment. Fortunately these capabilities have become available in hire end appliances, so the custom builds deployed for the demonstration will not be needed.

Recommendations for how that capability should be met in a full DWP deployment

Specific capabilities for the hardware that is needed to meet this capability is described in section 5.b, "Requirements for commercial off the shelf products to replace prototyped components.

Success Criteria

Containment Architecture

As part of the Smart Grid Demonstration project the Department of Water and Power successfully deployed various containment technologies, including a front end firewall mediating access from the internet to all DWP assets, the deployment of virtual local area network (VLAN) containment between zones within the DWP network infrastructure and SmartGrid zones, a Cyber Security (CS) Firewall which monitored flows between smart grid zones and would respond to event detected by the detection diagnosis and remediation infrastructure to cut off or rate limit flows, and data-power appliances which served as an application layer firewall capable to enforcing policies on the flow of information between the corporate zone, demand response infrastructure, and AMI zones in the SGRDP deployment.

The purpose of this section is to describe the successfully installed capabilities that were deployed on the SGRDP, so that the success criteria met in this demonstration can be applied to containment technologies to be deployed in future fully scaled Smart Grid deployments.

These capabilities were developed to demonstrate a proof of concept for securing software servers connected across zones, with the expectation that a fully scaled deployment would require off the shelf commercial products that are expected to support such capability in coming years.

2.1 Containment Regions Successfully Configured

Communications in the SGRDP are restricted to flows that are described in the fault containment regions form the original design as described in figure 2 (earlier). While the structure of the flows is apparent from figure 2, a better enumerated list of flows is available from a flow diagram constructed by the

Power Engineering Project Management Office (PEPMO) during the deployment phase of the demonstration, as shown in figure 3:

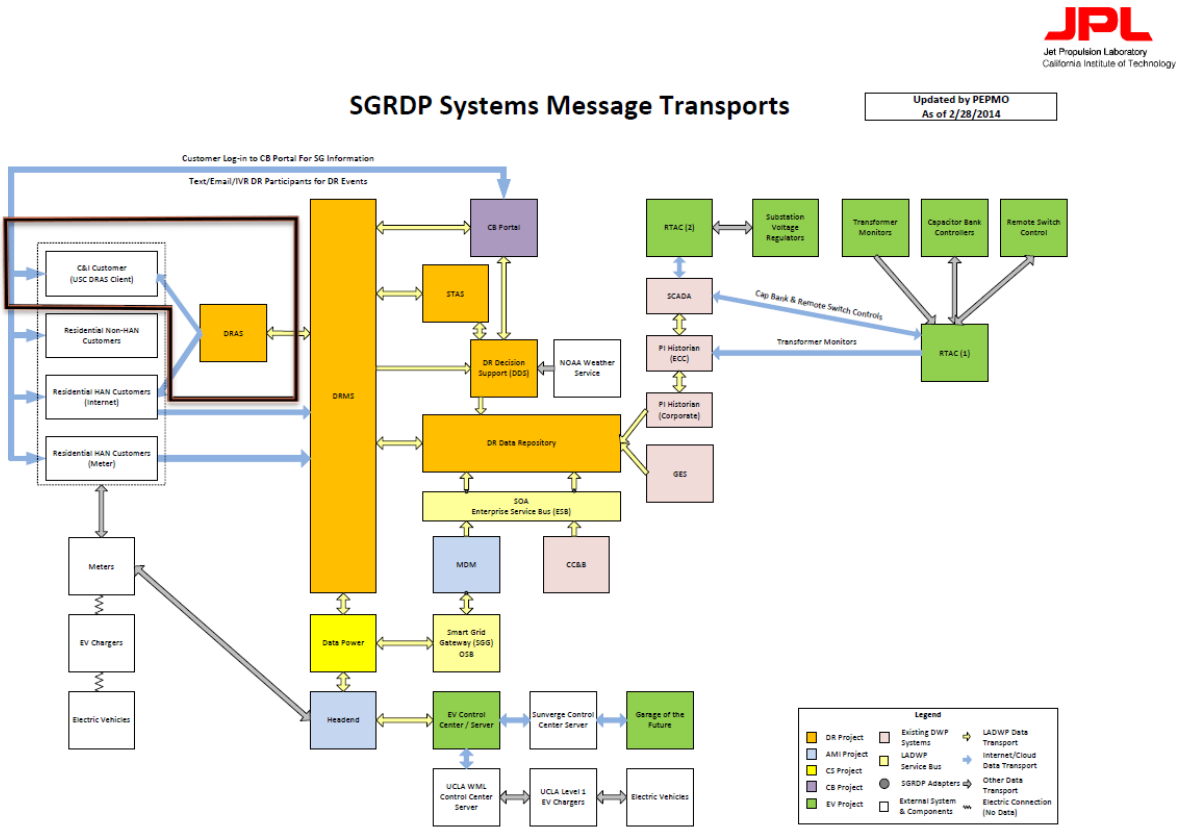


Figure 3: SGRDP Systems Message Transports.

These flows are augmented with additional management flows that support monitoring and control in the cybersecurity domain, as shown in figure 4.

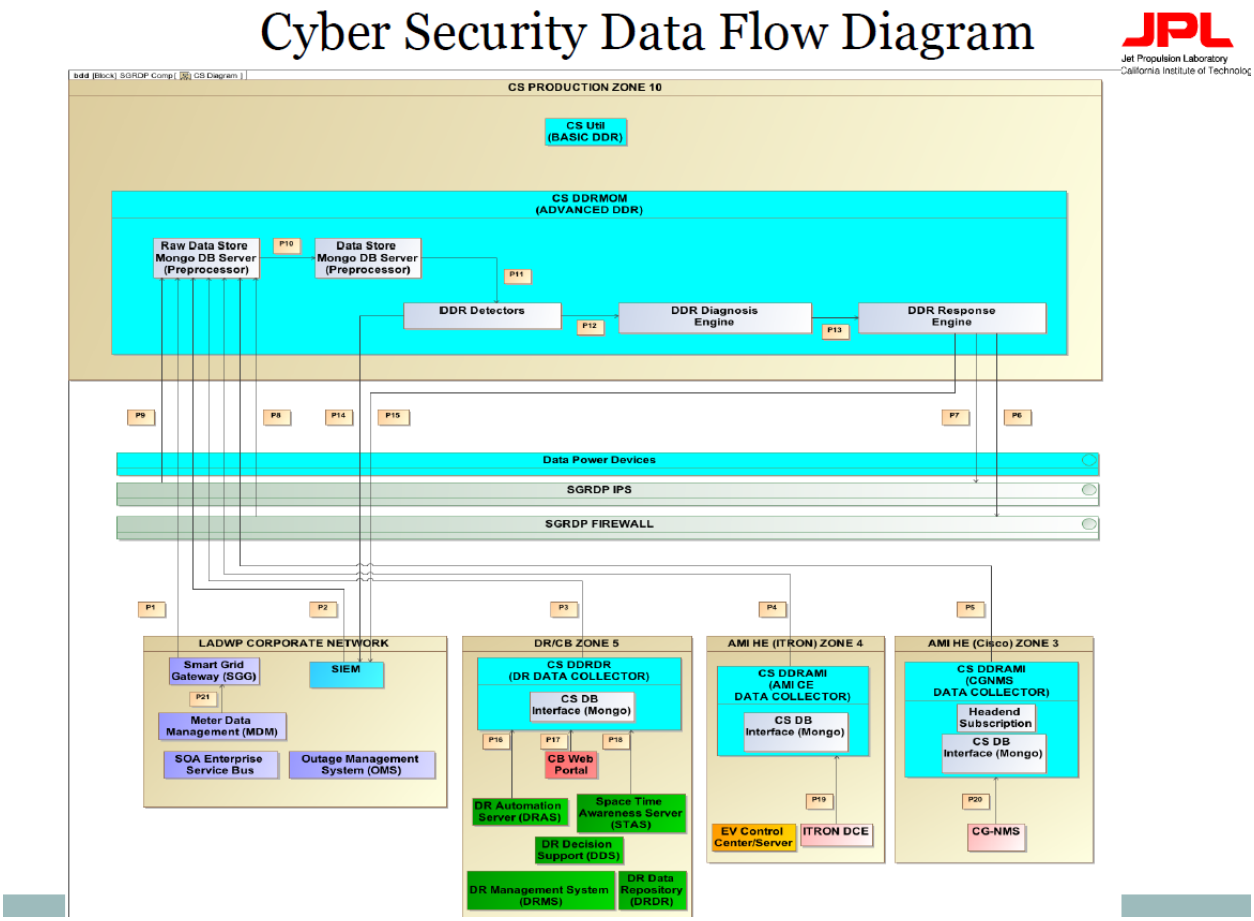


Figure 4: Cyber Security Data Flow Diagram

To simplify the network configuration, certain fault containment zone from the original diagram have been aggregated into related zones as described in figure 5

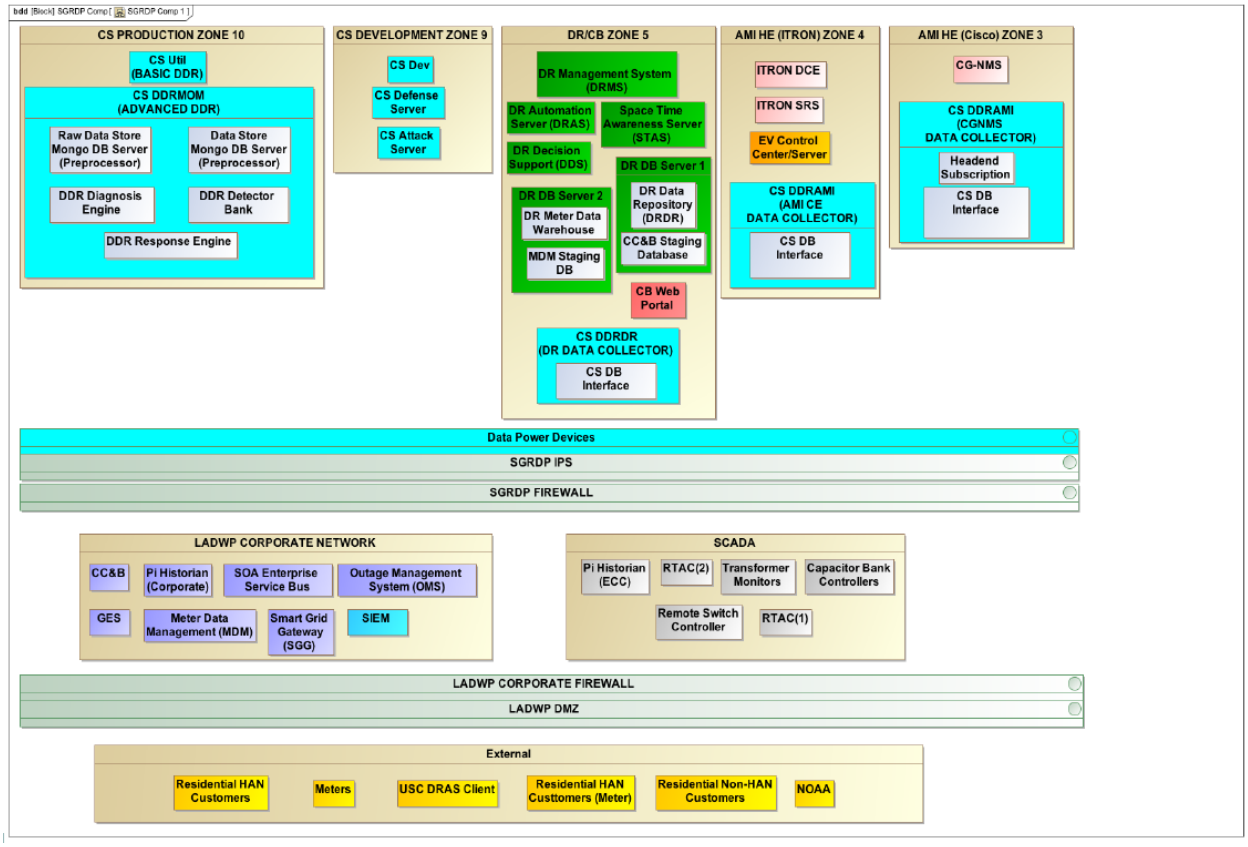


Figure 5

It is the purpose of the containment architecture to limit flows to only those described in the PEPMO diagram, to monitor those flows for indicators of malicious or erroneous activity, and to shut down or rate limit those malicious or erroneous flows as appropriate.

Description of zones successfully configured

As deployed, the following network zones are present:

DWP Corporate Zone

This zone includes the network and system components present at DWP that are separate from the smart grid demonstration project, including billing, customer service, dispatch and related functions. Only specific information needed by the demonstration project is to flow into smart grid domains, and an application firewall (the DataPower device) is used to manage live flows into and out of this domain from the demonstration. The success criteria for configuring separate containment zones would have to ensure components within the SGRDP did not have uncontrolled access to systems and data within the corporate zone, and this restriction on access applies also to the security components of the SGRDP. The description herein discusses the means by which this was successfully implemented so that the corporate zone remains protected from the

SGRDP zones. SCADA systems within DWP are located in a separate zone managed and protected by DWP to and from which there is no communication to the SGRDP, hence that zone is not described further in this report.

SGRDP Cyber Security Zone

This zone contains the computer security infrastructural components including the Detection, Diagnosis, and Remediation database and the computational components comprising the detector bank, and the diagnosis and remediation engines. Components that communicate with this zone include the entire SGRDP (excluding the corporate zone). Data flows into this zone from collection components placed on other systems throughout the SGRDP, and remediation actions are read from this zone by other SGRDP components, including certain firewalls and other containment mechanisms. The diagram of zones shows a security development zone, which is for development only and is not used in the production environment. The issues surrounding communication to that zone are the same as for the primary cyber security zone.

Advanced Metering Infrastructure (AMI) Zone

This zone comprises network and system components needed to communicate and process information to and from the advanced metering infrastructure, including meters, CGR's, and the head end systems which collect data from and communicate to meters either through cellular infrastructure, or through CGR's and a mesh network. Though each meter and CGR has its own associated security domain, they are treated here collectively, based on the type of device. Communication between CGR's and the head end is tunneled through parts of DWP corporate infrastructure.

SG Application Zone (Demand Response, CB, EV, etc.)

This zone comprises the systems developed for demand response, electric vehicle control, and customer behavior analysis and interaction. These systems have constrained communication with elements in the customer zone, or on the internet, and those channels must be monitored to detect attacks such as denial of service. Communication with other parts of the SGRDP that are not cataloged flows must be blocked. Communication to customer networks, and customers on the internet must be encrypted, preventing deep inspection at containment boundaries, so filtering and detection components must be installed at the decryption point for those encrypted flows.

Internet

This zone is not controlled by DWP but is identified as the end point of certain flows from other components. The SGRDP depends on communication with customers, whether through connections to the web portal by customer browsers, or to the customer gateway through open ADR. Communication between CGR's, or cellular meters and the head end may also transit networks that are beyond the control of LA DWP. There is little that can be done by DWP to ensure security and resilience of the open internet, but the impact can be mitigated through encryption and redundancy. These techniques are described for the zones that utilize the internet for communication.

Customer networks

This zone comprises the network and system components present in the customer zone. The Smart Grid has many customers, and these requirements are placed primarily on the interaction of these systems with systems in the utility zones. Evaluation is to be performed with the understanding that we cannot control the local configuration of systems within customer zones except by placing constraints on their interactions with DWP managed zones.

Observations

Containment Regions – The 11 fault containment regions in the design were reduced to 4 zones (plus the internet and customer premises). This was done to ease management of the network and reduce the number of required gateway interfaces. That was done at the expense of our ability to manage in mediate flows between devices in the same network zone. If the number of zones is not increased to match fault containment regions, then a distributed host based firewall technology could be deployed to manage the flows within network zones, limiting them to the authorized flows in appendix A.

System of Systems Impact – A better universally understood set of goals for the system of systems that constitutes a smart grid would have allowed for easier deployment of security technologies through the system. Because different parts of the system were developed almost independently, and then integrated, developers of component technologies believed that if they could secure their component in isolation using techniques that might be less intrusive, that their component could operate according to their specification, and that would constitute a successful demonstration.

For example, the goal of the statistical analysis components (STAS) of the demand response system is met if it properly processes input data and yields correct outputs. A better goal would be to ensure that the system as a whole continues to provide power, and this requires the ability to assess the accuracy of the data on which the prediction tools operate and the inputs to the prediction capability. While the Cybersecurity group focused on the system of systems impact as described, integration of our tools with the other parts of the project required actions on their part which were not a priority.

System Integration and Concurrent Design/Development – For a deployment at scale, significant effort must be applied to system integration from day one. Much of the development in the demonstration was targeted to point technologies and insufficient guidance and control were applied to system integration. The security group pointed this out early in the design process, and to the extent possible provided assistance in developing a consistent system architecture. What was needed earlier in the project was a strong commitment to use of technologies developed from within the cyber security team by other parts of the project, and this resulted in inconsistent application of identity management and system monitoring capabilities.

Special capabilities – There are important requirements dictated by the security architecture for the SmartGrid demonstration which must be present in products for a scaled deployment of the smart grid include:

a) Traffic Monitoring – The ability to communicate events to the smart grid detection, diagnosis, and remediation components. Some existing commercial containment appliances have such a capability so this is a requirement on selection of the appliances and configuration to communicate event data to the proper location. Such communication does not need to be direct, but may be relayed through corporate SIEM components.

b) Adaptive filtering based on communicated policy changes generated by the DDR infrastructure. This capability may limit the choice of appliances, but the capability might not be needed in all devices – rather it can be limited to devices between specific zones and containment regions.

c) Rate limitation for specifically identified flows. This limitation can be configured statically based on calculate maximum rates for the authorized flows identified for the smart grid, or the limitation may be specified dynamically in response to detected attacks for failure in the system. This capability does not need to be present in all containment devices, but is needed in at least one device along paths from the internet to internal smart zones, and between smart grid zones. This capability was present in the demonstrated deployment of the CS firewall, when demonstrated on the unscaled demonstration network.

The above capabilities are needed in addition to the performance requirements based on the projected volume of data that will be present. The performance requirements are likely the easiest to meet from off the shelf hardware, but once choice of hardware may be limited by the other requirements specified above.

5. Results

As a demonstration project, a critical goal of the LADWP Smart Grid Demonstration project was to learn what worked, and what didn't and to suggest improvements that must be made during a larger scale deployment. The results with respect to the security deployment for the Smart Grid demonstration are covered in the paragraphs that follow.

Containment Technologies – The strongest attack defense applied within the demonstration project was met by configuring the separation of systems into containment regions. In the demonstration, this was of particular importance to allow development of technologies by University Researchers while maintaining the security of the Department of Water and Power's existing operational systems. During the demonstration, the containment was successfully implemented by separating systems into 4 zones, and through the use of firewall devices at the boundaries of those zones.

If the security group had greater operational control of the individual systems within each zone (which was not possible in the demonstration because of continued development of the smart grid

technologies by researchers), it would have been more effective and less prone to errors in managing containment at the granularity of pairs of communicating hosts according the authorized data flows shown in appendix A.

This could have been managed through embedded firewalls on the network interface cards to each system, managed in a distributed fashion (a distributed embedded firewall). Firewalls within the network infrastructure would still be necessary as a second line of defense and to mitigate certain denial of service type attacks.

Attack Visibility – One of the gaps with respect to the development of the detection, diagnosis, and remediation rules was the absence of realistic attack data on which the diagnosis engine could operate. An initial part of the problem was that probes and attacks were effectively stopped by the outer perimeter defenses deployed by the LADWP corporate firewalls systems, and this traffic was not making it to the internal defenses for assessment and analysis. This was eventually addressed by providing for the flow of some of this attack traffic to and through the corporate SIEM.

This traffic, however, was of the nature of network background attacks, rather than any attacks specifically targeting the smart grid demonstration. Because of the limited scale of the demonstration, the system did not meet the goal of attracting specifically targeted attacks, and the development and testing of the detection, diagnosis and remediation components was instead limited to simulated attacks where events were inserted into the DDR data stream for processing.

The lack of a second testbed on which to evaluate the effectiveness of the DDR component further limited the kinds of testing to insertion of simulated attack records for any test that would be predicated on the loss of power to testbed users that were operation within the SGRDP.

Configuration Management – Another gap was in the configuration management process. A central authority must be responsible for configuration management on all deployed systems within a smart grid deployment. Because of the structure of the development organization(s) within the demonstration, it was difficult to apply common configurations across the systems used for different aspects of the project (especially the electric vehicle and demand response components).

This created problems with respect to deployment and operation of the endpoint security services, including the system integrity monitor, and for tools that collected event information for analysis within the detection, diagnosis, and remediation components of the system. Effective deployment (and effective development) of these security technologies requires a stronger central configuration management component for the system.

System Integrity Monitor – The system integrity monitor was successfully deployed in the final stages of the project. System compromises such as the altering of system files on Linux and Windows operation systems was analyzed and successfully tested. The file integrity checkers is an important capability in intrusion detection, diagnosis, and remediation. The goal of designing and developing a policy based integrity tool that monitored integrity of the SGRDP system components, detected unauthorized modifications, and communicated changes to the CS zone was met.

Acknowledgements

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Appendix A

Plan for Vulnerability Assessment and Penetration Testing (VAPT) of Smart Grid LADWP

a. Overview of VAPT Process



b. Overview of Tools

Acunetix	Web Application Security Scanner
BurpSuite	Web Application Security Scanner
Veracode	Application security mobile, web and 3rd party apps.
NMap	Network Scanning and debugging
Wireshark	Network protocol analyzer for Unix and Windows.
NeXpose	Vulnerability Management Software
Nessus	Vulnerability Scanner on Network and applications
Metasploit	Penetration Testing tool
FOCA	Tool to find metadata and hidden information in the documents its scans.
Scapy or Tamper	Packet Generation and Manipulation Program
Fuzzer	Manipulating network protocol manipulation
AirGrab	Wireless network scanning tool
Wi-Fi radar	Wireless network scanning tool
Acrylic Wi-Fi	Wireless network scanning tool
Aircrack-ng	Wireless network scanning tool
Angry IP scanner	Network Scanning

Netcat	Network Scanning and debugging
Nikto2	Network Scanning and debugging
Sulley	Fuzzing framework for fuzzing files, network protocols CLAs etc.

Overview of Common Vulnerabilities (but not limited to)

Injection Attacks	**Directory Listing**
Cross Site Scripting	**Cross Site Request Forgery**
Buffer Overflow	**Sensitive Data exposure**
Invalid Redirects	**Insecure data Storage**
Security Misconfiguration	**Insecure Authentication**
Remote or local file inclusion	**Code Tampering**

VAPT Strategies

The LADWP Smart Grid (SG) cyber security capability can be evaluated in different ways depending on the type of information that test team has. Pen testing approaches should be used:

1. **External VAPT** (how an adversary from outside the system can compromise the system's capabilities)
2. **Internal VAPT** (find internal flaws which can be used by a disgruntled employee to perform damage on the system and by the external attacker to gain privileges once he is inside the system.)

The motive to perform VAPT from outside is to identify the attack paths and vulnerabilities when attackers have no or limited information about the target organization. It is important to make such a distinction between approaches because the first step of VAPT methodology will change if we change the strategy. For external VAPT, the test team does not know about the network infrastructure and may have some information about the DNS servers or email servers of the organization. They perform network scanning to identify hosts across the system and to understand the network topology and their functions. For internal VAPT, the test team already knows the network topology and set of services; they start with finding the vulnerabilities of the system as their first step, which is the second phase of the external VAPT. The test team considers the overall security of the system by performing the testing from different endpoints. VA should be carried out in two ways: unauthenticated VA and authenticated VA. In the former one, automated tools without credentials are used and in the latter one, automated tools with credentials are used. This difference distinguishes between the attacks performed by an outsider and insider (disgruntled employee). The team may find different attack paths in both the approaches which are otherwise not highlighted. Before moving forward to describe the methodology, we should define the scope of the VAPT process.

Scope

The test team should perform penetration testing of the SG infrastructure at a regular interval or whenever there is a system upgrade or patch. It is important to define the scope and stakeholders involved in the process of VAPT. Pen test can be performed on multiple components simultaneously or on a single part of the overall SG for instance AMI infrastructure. The pen testers can also evaluate the cyber security capability of the cyber-physical system by which they can understand the interaction between the cyber and physical components. During the penetration testing process, test team should inform and take permissions from the stakeholders of the assets on which testing performed. Divide the pen testing into different phases depending on which system you are choosing to perform pen test.

1. Select a zone and perform penetration testing on its components from inside and outside if connected to the public domain.
2. Understand the interaction among the components and vulnerabilities associated with them. In this step one assesses whether identified vulnerabilities can be exploited by an attacker to compromise targets systems or gain access to sensitive information.
3. After penetration testing, perform testing between zones and their components.
4. Understand the interaction among the various zones and attack paths crosses different zones. In this step, one determines whether privilege escalation may be used to gains access to sensitive DWP services and database.
5. Assess the capabilities of the system to detect attacks. A system may be vulnerable to attacks specified in the first 4 phases, yet the impact of such an attacks will be greater if the attack succeeds, and further if it goes undetected. Testers might repeat a successful, but detected attack a second time while modifying their technique to prevent detection.

There are number of areas to cover within the DWP SG capability:

1. Data security
2. Server security
3. Communications security
4. Wireless security
5. Cross zone security includes all above
6. Physical security

For the internal network, since everything is already known, testers should perform configuration review of the applications, servers, firewalls and other system components to validate whether they comply with the requirements of the smart grid. The interaction among different zones within the organization should be assessed based on the requirements of the organization. The test team should perform an external assessment on the network when a system is connected to public domain. The pen team should try to explore as many paths as possible depending on their scope, time, and capability.

Understanding Targets

The smart grid system is the combination of many federated systems. Therefore, the first step is to list and understand all federated systems which are relevant to the stakeholders of the system. In the case of the SG, the stakeholders are DWP personnel, customers, government, etc. and the systems are those zones which can be attacked by an adversary to disrupt the functioning of the SG.

1. DWP corporate zone
2. SGRDP cyber security zone
3. AMI zone
4. Smart grid application zone (electric vehicle etc.)
5. Customer Networks etc.

The pen testers should understand these systems and their interaction to gain in-depth knowledge about the system. Once they have understood the SG zones, they need to classify the data and its format between and within different zones. The data resides in three places:

1. At rest (databases)
2. At end points (employees' desktops, customer meters, etc.)
3. Travelling across communication channel

To protect the data in all three states, one should understand the dynamics of the data, who are the users who will access what type of data and how. The test team should verify such questions across all the zones. For instance, the customer electricity consumption data which is communicated from the client's network via AMI zone to the SCADA system in a particular format. The pen testers should verify whether customer data is traveled safely (CIA) across different zones, protected at the customer endpoint from cyber intrusion and stored safely at the DWP databases. If they do not protect customer consumption data, it can provide many holes to breach customer privacy. Now we will describe the steps of pen test which should be performed to demonstrate the security of the smart grid.

Foot printing/Reconnaissance

From external point of view (when testers don't have information about the system)

Start with passive scanning where the test team can use tools like **ARIN** and **WHOIS** to know information about the top level domain and IP addresses of the target (Over here we have assumed that testers have no information about the target just like an adversary). WHOIS can reveal important things about the corporate network of DWP such as who is the registrar, some name servers, and their names, admin information etc. Once testers figure out the network IP addresses or they already have the IP addresses such as in targeted VAPT; they should perform active scanning. Active scanning involves scanning the channels directly to identify the hosts in the network and services running on them. The process of scanning is categorized into three phases:

1. Network Scanning
2. Port Scanning
3. Vulnerability Scanning

Network scanning is performed when testers don't have information about the network topology, hosts deployed and services are running on them. The tools which can be used to perform network scanning are ***Nessus, Advance IP scanner, Netcat, etc***. Once you have the information regarding the hosts in the network, the next step is to find out what are the services running on the hosts and whether they are accessible over the network. The test team should perform **port scanning** to gain above information. It is important to understand whether ports are accessible or not. If yes, what services are running on them? The testers should classify the ports corresponding to each host as open, closed, filtered and open-filtered. The tools to perform port scanning are ***Network Mapper (Nmap) and Netcat.*** Nmap is the most common tool used to perform port scanning. For scanning the wireless network, the tools are ***AirGrab Wi-Fi radar, Acrylic Wi-Fi, Aircrack-ng and Wireshark for traffic analysis***, etc.

Example: AMI zone is divided into three sub-zones: 1) meter zones, 2) communication zones and 3) head-end equipment zones. The test team should perform network scanning to identify meters over the network, which communication protocol they are using, what is the data format of the messages etc., how the data is handled at the head end, head end system description, etc. If they can get enough information regarding AMI network, they can find out the vulnerabilities of the system.

Vulnerability scanning/assessment (VA) involves scanning the services running on the hosts to see whether they have software bugs or not which can be exploited to gain access. The vulnerabilities are associated with different software components: web application vulnerabilities, OS vulnerabilities, web server vulnerabilities, etc. For different types of systems, different tools are used. For a web application VA, ***Acunetix, BurpSuite, w3af*** are some of the tools. For a web server VA, ***Nikto2, Nessus*** can be used.

The scanning should be performed from outside the organization without credentials and limited information. The end points in the LADWP SG infrastructure from scanning should be performed:

1. DR web portal server
2. DR application proxy server
3. CRM
4. DRDR for find the injection attacks
5. MDM
6. ECC and OMS
7. SCADA system servers
8. Vendor specific head
9. Head end smart sync
10. USC and UCLA control centers
11. Customer's network (home area and industrial)

It is also important to scan for possible malware insertion points on end nodes, including mobile devices, workstations, and terminals. For instance, an adversary can send phishing emails containing malware (Word or Excel macros) to the relevant employees. Once malware is installed on the victim's device, it may back connect to the attacker's device and then the attacker can access it remotely and escalate its privileges. A similar attack was performed last year on the Ukraine Smart Grid. It is important to understand the behavior indicators of malware such as Memory corruption, Remote Code Execution, Changes in File Configuration, and Privilege Escalation when an attack is underway. One must perform web filtering and implement network-based malware detection tools before an attack is performed. After an attack, techniques for Data loss prevention (DLP) and containment of the compromised architecture should be applied to block incoming traffic and to ensure safety of the network. Employees must be educated not to open emails from unknown sources, which is a part of Social engineering program.

The pen team should use a CVSS scoring mechanism to understand the impact of the identified vulnerabilities. CVSS system performs scoring on the basis of different parameters such as Confidentiality, access control, availability, etc. It will help them to examine the identified vulnerabilities to determine whether they can be exploited by an attacker to compromise targeted systems or used to gain access to sensitive information. They can refer to the database maintained by the security organizations such as Symantec to understand the consequences of the vulnerability compromise.

For example, typical university style scoring may be applied with each component provided a letter grade where a grade of A indicates excellent capability, a B is acceptable, and C, D or F indicate insufficient controls have been applied at progressively greater levels of deficiency. Components that should be assessed are Host Security for each class of platform on which the system is deployed. Given the uneven access that has been provided to the security team by EV, DR, etc., each part of the smart grid project should receive a separate grade for host security. Each smart grid application should receive a separate grade, independent of the grade for the host on which the application runs. Finally, scores should be provided for Network configuration, and for Incident Monitoring.

The output of such scanning will provide information including but not limited to:

1 List of host and network devices in the network and their identifiers such as IP address, accessible or not etc.
1. OS running on the hosts
2 List the ports on the hosts which are accessible from over the internet (outside the organization).
3 Services they are running over which protocols and ports
4 Version of the services which states whether they are patched or not
5 Identify which network protocols they are running (in LAN, HAN, and wireless mesh network)
6 A list of endpoint onto which malware can be potentially installed

From an internal point of view

The testers have access to the internal network of the smart grid. The primary motive is to understand how an employee of the DWP can perform malicious activities on the network, what the attack paths he can choose are and how he can leverage his knowledge and privileges about the system to launch a cyber-attack. The internal reconnaissance includes understanding: ***directory services, authentication methods, identifying sensitive hosts, etc***. Apart from these security configuration validations, they should perform above scanning techniques to find the bugs from inside the organization since typically both types of testing have same targets.

Social Engineering Attacks for information gathering

With a motive to gather information about the system, attackers also perform social engineering attacks. SE is an art of convincing people to reveal confidential information. It is worth mentioning that attackers can perform social engineering attacks in different ways: ***human based, computer based (phishing) and mobile based (malicious mobile apps on the mobile app store)***. They can perform attacks by:

1. Contacting DWP employee over the telephone to gain confidential information.
2. Phishing emails with attached Trojan horses or other malware and tricking users to click on to email links.
3. Stealing smart grid employee's laptops or phone to gather info.
4. Leaving USBs, which contain malware at strategic locations within the smart grid environment.
5. Pretexting is another kind of social engineering attack.
6. Interacting with the vendors (of smart meters, PLCs, etc.) to gain credentials, communication keys or device configurations.

Such attacks are possible because of

1. Insufficient security training

2. Easy access to the information
3. Federated systems such as in smart grid
4. It's hard to detect such attacks

Since the smart grid is a cyber-physical system which has many cyber and physical components from different vendors, an adversary can contact any component vendor to gain its configuration information or default passwords. Usually, attackers identify the victims of the SE attack, they develop relationships, and then they exploit that relationship.

Recommendation to combat SE attacks are as follows:

1. Educate employees regarding social engineering attacks
2. Do not open emails from untrusted sources
3. Ask employees to read DWP policies and guidelines
4. Implement Mobile data management solutions to manage BYOD devices.
5. Educate vendors about SE attacks
6. Test the configuration of the mail servers for spam emails.

Server Assessment

It is important to understand the security capability deployed to protect the servers of the SG. The servers are responsible for providing services to the DWP personnel, customers, vendors, etc. and perform a variety of SG functionality. In the LADWP different servers and control centers are deployed for various features. Some of them are:

1. Web portal server for DR
2. DR application proxy server
3. USC control center
4. UCLA control center
5. SG EV control center
6. Head end smart sync
7. Vendor's head ends
8. SCADA server
9. ECC server

In the case of DR, it is important to analyze the DR server application to the DRAS, DR UCLA, and USC application, ECC on the BAS, MDM web interface, Vendor particular head-end interface, etc. In server pen test, testers should identify the application process and functionalities which are exposed to the

users. They should model the process that is followed by the users and identify the dependencies among different components of the application. Once this has been performed, tester should find out the vulnerabilities in the applications by performing:

1. Configuration testing *(for internal testers)*
    - Ensure that HTTP open sessions time out at a reasonable time.
    - Perform assessment of the Injection attacks.
    - IDS and Firewall configuration testing
    - Ensure that default accounts are not present.
    - Ensure that TCP timeout at a reasonable time.
2. Authentication and session management *(for internal testers)*
3. Access controls implemented *(for internal testers)*
4. Secure code review *(for internal testers)*
5. Identify the OS, applications running, ports accessible on the server. *(for external testers)*
6. Identify vulnerabilities and validate them using the VAPT process defined above. *(for external testers)*
7. The tester should use automated tools such as Acunetix, BurpSuite, Veracode, etc.
8. Once vulnerabilities are identified, testers should perform vulnerability exploitation by either automated tools such as Backtrack environment, Metasploit or manually.

The number of server attacks is possible such as ***server rooting, web hijacking, DNS cache poisoning, access control breach, session hijacking, etc***. When scanning is performed on a server, sometimes it reveals confidential information about the server configuration of the server, firewalls installed, access control, etc. The information can be present in the error responses, messages transferred, web pages displayed, client-side scripts, etc. If so, there is an information leak which will help attackers to gain knowledge of the server. It is also important to analyze:

1. The web interface
2. The web message protocols such as SOAP or REST
3. The client side applications interacting with the DER, CIS, vendors, EV management server, etc.

Network Communication Testing

The network communication of the smart grid system is responsible for maintaining the situational awareness, sending control signals to the field devices, cyber security functions, DR, managing interaction between the cyber network and physical network. The target in the network communication includes the wireless network, network protocols, etc. The primary purpose is to understand the network interface, identify the vulnerabilities associated with the system which provides access to attackers to compromise the communications in the smart grid. The tools to perform network scanning are ***Scapy, Wireshark, USRP2, Ettercap, Sulley,*** etc. The pen testers should divide the scanning into

different phases corresponding to each subsystem. Such systems and communication between components are as follows, and as described in greater detail in appendix A cited earlier from the containment section of this document:

In case of DR, the communications between

1. Energy resource and data collection units (DCUs),
2. DCU and service gateway,
3. DDS to DRDR,
4. GIS to STAS,
5. Energy resource and service gateway.
6. Web portal server and home router
7. DR proxy server and home router

In case of AMI, the communication between:

1. Itron billing usage and home router,
2. Head end and smart meters
3. Smart meters and EV chargers
4. EV chargers and service gateways
5. Smart meters and data collection units

In case of LADWP power zone, the communication between:

1. Power generation devices and ECC
2. ECC and SCADA system
3. ECC and DWP OMS
4. Power generation and switching station
5. ECC and OSI historian

In case of LADWP business zone, the communication between:

1. OMS and ECC
2. OMS and CIS
3. OSI and MDM
4. DEW and MDM
5. ECC and DEW
6. OMS and GIS
7. MDM and vendor particular head end

For instance, communication between the meter and AMI head end. Another example is communication between ECC and OMS, which occurs regularly to predict the demand patterns. The testers should perform all sorts of tests which involves data integrity checks, customer privacy, DDOS attacks, generation control checks, etc. It is imperative to ensure that all the inputs from outside the system to inside the systems are verified correctly, and internal system configuration should have reviewed thoroughly. Since the smart grid is connected the UCLA and USC networks for power delivery and other relevant functions, it is possible that there is some path from those systems to the smart grid facility. So it is important to understand and analyze the communication between these systems. The communication path between:

1. DR proxy server and UCLA service gateway
2. DR proxy server and USC service gateway
3. Within UCLA and USC networks

Another example is of LADWP business zone that communicates with many components over the internet and intranet. It manages customer information, power management, demand response function, etc. If an adversary can enter into such system, he is likely to access other systems as well. Some the targets for the smart grid domain are as follows:

1. Demand response: cryptographic keys used in the communications with ECMS and DRAS, software installed on the field devices such as data collection units, etc.
2. AMI: C12.18 passwords for optical ports, cryptographic keys used in the communication, software installed at devices such as PLCs, meters, aggregators, etc.
3. OSI historian that can be accessed from the internet if there is a path from the internet to MDM to a historian. If there is an SQL injection vulnerability in the web application implemented for MDM, there is a path to a historian. Similar to CIS and MDM.

The pen testers should perform variety of tasks to analyze the weakness in the communication network:

1. Traffic capture: It helps the red team to understand the information which can be leaked from the standard traffic monitoring. (Wireshark)
2. Network Protocol cryptographic keys analysis
3. Protocol Fuzzing and vulnerability exploitation (Ettercap)
4. Test and Review firewall and IDS configurations (FireHOL tool for firewalls)
5. Keep track of routers which are public domain facing

Cyber-Physical Attacks Pen Test

While considering traditional security evaluation of the smart grid, it is important to evaluate the security capability from a cyber-physical point of view. An activity performed in the cyber domain can affect the physical infrastructure or vice versa. The different types of attack scenarios are possible in case of such cyber-physical systems:

1. Physical-Physical
2. Cyber-physical
3. Physical-Cyber
4. Cyber-cyber
5. Cyber-physical-cyber
6. Physical-cyber-physical

There are a number of locations in the smart grid facility from where such attack scenarios may arise. Such attacks can be performed by an adversary or disgruntled employee by misusing his privileges. The zones which are important to access are:

1. Demand response
2. Electric charge vehicles
3. SCADA system
4. Control servers etc.
5. Home meters and commercial customers

The ultimate goal of the attacker is to affect the functionality of the smart grid that is power delivery. The testers should perform testing by analyzing the security of system on the basis of a functionality they are targeting. They should abstract the attack path and find out how much resilient the system is if attackers are able to compromise control systems. It is not trivial to perform and evaluate the security capability of such critical system in real time. In such cases, pen team should minimize the scope of test to a particular functionality and setup a system corresponding to it. Before giving an example of a setup, it is important to understand different variety of cyber-physical attacks:

1. Load Drop attack
2. False data injection attacks compromising the integrity
3. DDOS attack communication infrastructure
4. Customer Privacy breaches
5. State estimation attacks

In the case of load drop attack, a sudden load drop in the system can cause power generators to trip resulting in a total or partial system shutdown and loss of power delivery to the customer. Need to evaluate the impact of a sudden drop of load on the system. The following process flow indicates the series of events which lead to power delivery failure.



Minor disturbances and contingencies such as generation loss cause the frequency to fluctuate, but as long as the system can prevent the rate from going out of the optimal operation region (59.97 – 60.03 Hz) and quickly recover to 60Hz, the system operates continuously. DR can be considered resilient if the required amount of load is always curtailed within a limited time, where the expected load and time are dependent on utility-specific requirements. The impact of variation of DR responses to the change of contingencies was analyzed. There are two inputs to the sensitivity analysis:

1. The size of the emergency that happens, which is a loss of individual MW of generation
2. The amount of load that responds to the crisis through DR. The metric that demonstrates system stability is the frequency of the system (Hz) (i.e. output of the sensitivity analysis).

The motive of false data injection attacks is to reduce the state information about the SG or to control some system components for malicious attack. For instance, increasing the frequency of the generators beyond a threshold and deceive the detector by injecting a payload for some malicious task. One of the examples of false data injection attacks is Sybil attacks where an adversary inserts a malicious node in the network which impersonates the real nodes to modify the data within the communication system. This attack is performed by inserting a malicious sensor in the network which is responsible for sending the updating the SCADA system with wrong readings about the state of the scheme.

A Possible Attack Scenario

An adversary performs a cyber-attack on the metering infrastructure of the customers' network; Itron field collection system will not able to collect appropriate meter readings. The meter readings indicate the amount of power consumed by the customers and predict the demand patterns. Since information is not collected on time or wrong information is collected, CIS is not updated at regular intervals. Because of which OMS is not able to make appropriate decisions demand patterns and outage prospects and therefore not able to instruct power generation component to generate more power to meet the unforeseen demand or during an outage. Such attacks can have cascading effects on the system components which ultimately affects the function delivery.

Setup of test environment for Cyber-physical security testing

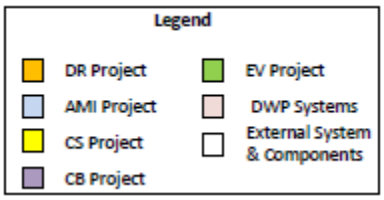
1. Define the functionality of the system which is the focus of the test. For examples, power generation, DR, EV, etc.
2. Imitate a small portion of the power system topology in some simulation software such as Power World.
3. Set up a communication network between sensors, control system, hardware components, etc. with appropriate protocols and data packets which are implemented in the real system.
4. Define a realistic attack path which is possible and exploit it to see the variation in the function delivery.
5. Observe which metrics are relevant for the resilience of the system providing specific service delivery.

Pen Test Conclusion

In the case of the internal penetration testing, the test team can simulate what an insider could accomplish. The target is same as the external penetration testing, but the major difference is that the test team has some authorized access within the system. The test team should also perform the external penetration testing to know what the attack paths from outside to inside the organization are. The test team should do most of the test as if one has inside information, and from machines that insiders might have access. On the other hand, the external tests (such as port scanning, a gathering of information, etc.) are performed to verify the availability of this information to an attacker, even though we will assume the attacker has this information when performing other tests.

Appendix A

SGRDP System & Interfaces



LADWP SGRDP Systems / Components	Status / Estimated Completion Date	Data Connection to/from (via Service Bus)	Connection Type / Interface (To & From)
DRAS		DRMS	M13 & M 12
		To: C&I Customer (USC DRAS Client)	Internet
		To: Residential HAN Customers (Internet)	Internet
DRMS		STAS	M17 & M16
		To: DR Decision Support (DDS)	M18
		DRAS	Repeated- See Above (M12 & M13)
		DR Data Repository	M26 & M25
		CB Portal	M22 & M22-1
		Data Power	
		From: Residential HAN Customers (Internet)	Internet
		From: Residential HAN Customers (Meter)	Direct (Cellular) or through CGR (Fiber or Cellular)
DR Data Repository		From: DR Decision Support (DDS)	M19
		DRMS	Repeated- See Above (M25 & M26)
		From: MDM (via ESB)	M4
		From: CC&B (via ESB)	M3
		From: PI Historian (Corporate)	M1
		From: GES	M2
DR Decision Support (DDS)		From: DRMS	Repeated- See Above (M18)
		STAS	M21 & M20
		To: DR Data Repository	Repeated- See Above (M19)
		CB Portal	M20, M21
		From: NOAA Weather Service	M24
STAS		DRMS	Repeated- See Above (M16 & M17)

MDM		To: DR Data Repository (via ESB)	Repeated- See Above (M4)
		Data Power (via SGG)	
Headend		Data Power	
		EV Control Center/Server	
		Meters	Direct (Cellular) or through CGR (Fiber or Cellular)
EV Control Center/Server		Headend	
		Sunverge Control Center Server	Internet
		UCLA WML Control Center Server	Internet
Garage of the Future		Sunverge Control Center Server	Internet
RTAC (1)		SCADA	Internet
		To: PI Historian (ECC)	Internet
		From: Transformer Monitors	AERIS via VPN Router
		Capacitor Bank Controllers	AT&T Cellular Network
		Remote Switch Control	AT&T Cellular Network
RTAC (2)		Substation Voltage Regulators	Connected inside DS-BB
		SCADA	Internet
Substation Voltage Regulators		RTAC (2)	
CB Portal		DRMS	Repeated- See Above (M22-1 & M22)
		DR Decision Support (DDS)	Repeated- See Above (M20, M21)
		C&I Customer (USC DRAS Client)	Internet (M23)
		Residential Non-HAN Customers	Internet (M23)
		Residential HAN Customers (Internet)	Internet (M23)
		Residential HAN Customers (Meter)	Internet (M23)
Data Power		DRMS	
		Headend	
		MDM (via ESB)	

Appendix U Technology Performance Report Use Case (Demonstration) #8

USC SGRDP-EV Project
Technology Performance Report

Use Case (Demonstration) #8

Demo/Use Case Name: Report on Battery Aggregation and Backfill Results

Brief Description:

The USC EV team evaluated interactions of: (a) stationary batteries and Grid during the stationary battery charging cycles; (b) stationary batteries and EV(s) during the EV(s) charging cycle; and (c) stationary batteries and Grid during the battery discharging cycles into the Grid.

There are three areas of consideration that are part of the Use Case 8: Battery Aggregation and Backfill demonstration. Based on the Design Document, these demonstrations include:

a) Use of EV Batteries in the Grid (G2V only);
b) Use of EV Batteries in the Grid (G2V & V2G); and
c) Distribution Effects of Battery Aggregation and Backfill (G2B, B2V, B2G).

Design Document Methodology

Assumptions

Charging aggregated EVs can result in the overload of transformers at the distribution level. Each EV consumes from two to ten times the amount of power of a single electric home during charging. Charge rates depend on levels of charging. Considering public adoption of Level 2 charging which requires 220 V and greater than 50 A of current, the amount of power that a single EV can possibly consume is very high. The challenge involved with EV integration is to balance that load when a large number of EVs need charging and working with the vehicles' onboard Battery Management System (BMS) to handle charging given that charging current varies nonlinearly with time and percent of charge. It is also important when considering an aggregate scenario to take into account consumer behavior. Periods of time exist during the day where EV loads could be heavy and optimization of charging schedules could limit issues created by severe loading. Identifying active charging stations and monitoring State of Charge (SOC) allows for greater flexibility of charging schedules. The control center system takes into account various criteria to turn on or off a charger to ensure safety and grid needs are met.

Demo Assumptions

The following assumptions have been made:

- In the approach, the USC EV team assumed the average power at 5 kW per house. IEEE 34 Bus has total power of 2 MW, which leads to 400 houses as the loads along IEEE 34 Bus System. Assume that level 2 charging has capacity of 8 kW (32A) at 240V with 6 hours to be fully charged.

- People will drive to work from 6-8 AM during which they can neither charge from the grid nor feed to the grid.
- People will drive back home from 5-8 PM during which they can neither charge from the grid nor feed to the grid.
- Before driving to work (6AM) and back home (8PM), people will have their EVs fully charged at 100% battery.
- Each trip, from home to work place, or from work place to home will use about 50% of the electricity, which is equivalent to 50% remaining battery.
- People will not use their EVs during work hours, from 8AM to 5PM.
- As soon as people arrived at work place or home, they will plug in their EVs ready for G2V or V2G.

Demo responsibilities

The EV Project team installed appropriate grid-tie inverters and bi-directional AMI smart meters at certain charging stations to demonstrate Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) operations. Depending on the make and model of the EV, battery backfill may not be possible without modifying the BMS and other circuits on the EV. The EV Project team studied and investigated a non-destructive approach to implement this demonstration. All EVs that are participating in the V2G demonstration may need to be equipped with additional circuits and modules.

Demo steps and flow

Data was collected from the project batteries during the charging and discharging cycles. Current, voltage, real and reactive power, frequency and harmonic data from the charging stations were used to model power flows on the distribution system for each of the scenarios.

1. Stationary Battery charging from the grid; typically at night (G2B).
2. Stationary Battery charging EVs; morning through evening hours (B2V).
3. Stationary Battery back-feeding into the grid; peak times, no EV charging (B2G).

Distribution system analysis originally focused on the following:

1. Utilization factor – the ratio of peak power demand to the maximum power that the system can accommodate.
2. Capacity factor – the ratio of peak power handling for a system component such as a transformer to the maximum power that the component can accommodate.
3. Load factor – the ratio of actual load to peak load.
4. Power factor – the ratio of real useable power that can perform work to the magnitude of apparent power (current times voltage).
5. Power quality – an overall rating of voltage and current wave shapes, frequency regulation, and noise or harmonic distortion levels.

The USC EV team calculated the previous five indices for the two circuits, 88-22 and 88-23, from Chatsworth distribution network.

As an example, Capacity Factor was calculated during the time the stationary battery is discharging into the Chatsworth system. The peak power generated from the battery was compared to the battery rating (capacity) to calculate the Capacity Factor.

Utilization Factor compared the peak load on the Chatsworth circuit to the rated size of the Chatsworth Substation transformer serving the load.

Load Factor compared the average load on the Chatsworth circuit to the peak load encountered during the demonstration period.

These indices provided an assessment of overall distribution system reliability, asset management, infrastructure optimization, and cost effectiveness.

Planned approach

1. Analyze and model collected data using the EDD, MATLAB, and PSCAD
2. Demonstrate the simulation of the distribution systems using EDD, MATLAB, and PSCAD
3. Finalize the demonstration report

Final Used Methodology

Key changes in Demo design and justification

To meet the general system modeling and representation requirements outline in the design document, the following activities were under taken by the USC EV research team:

1. Two sets of distribution network models were selected to enable analysis of EV distribution effects as described in the SGRDP Preliminary Design Document. Furthermore, three software programs were selected for the development of these models. These software programs are:

    a. Distribution system modeling software Distribution Engineering Workstation (DEW) by Electrical Distribution Design, Inc. (EDD) is used to model the distribution network to assess the impact of EV, customer energy storage systems (CES), and distributed generation (DG) such as photovoltaic (PV) on the grid with regard to system load flow, and load factor including the fully functional microgrid. EDD is specialized in doing power system analysis on distributed level systems but has limited capability in running harmonic and real-time analysis. Power flow analysis and load factor results are expected from EDD.

    b. Mathematical modeling and analysis tool MATLAB and Microsoft Excel were used to model and analyze various charging and discharging strategies associated with EV, CES, PV, and the Grid. These software were expected to perform designed charging/discharging algorithms of batteries.

    c. Electromagnetic time domain transient simulation software Power System Computer Aided Design (PSCAD) by Manitoba Hydro was used to model high-frequency transients to assess the impact of multiple Level 2 EV chargers on the electric network. PSCAD was used to perform power quality analysis for IEEE 34 system. The university version of PSCAD had limited buses restrictions and could not be used to build Chatsworth system. IEEE 34 system results were used to meet the demonstration requirement.

2. Since EDD is a newly developed software and not many tests have been made using this software, two distribution network models were selected to compare with the benchmark results and have a more reliable analysis for the Chatsworth system. These two systems were:

    a. An IEEE 34 bus test system reflecting an industry standard distribution test model

    b. A Chatsworth Distribution System or microgrid representing a residential/industrial area in the LADWP system with a special focus to the circuit numbers 22 and 23

3. The EDD, Matlab, and PSCAD models and the two system representations (IEEE 34 bus and Chatsworth) allowed the attachment of multiple EV-charger loads of various classifications

4. A harmonic and sensitivity analysis were setup on the test systems with the goal of revealing the substations within the LADWP territory that have the greatest impact on the transmission grid when they were similarly subjected to EV loads.

Technologies Deployed

List of systems/equipment deployment

Two distribution network models were selected to compare with the benchmark results and have a more reliable analysis for the Chatsworth system. These two systems were:

- An IEEE 34 bus test system reflecting an industry standard distribution test model

- A Chatsworth Distribution System or microgrid representing a residential/industrial area in the LADWP system with a special focus to the circuit numbers 22 and 23

Success Criteria

Description of success criteria for this Demo

1. Develop models of Chatsworth using EDD

2. Test G2V, G2B, B2V, B2G and V2G strategy using EDD model

3. Use mathematical modeling and analysis tool MATLAB and Microsoft Excel to model and analyze various charging and discharging strategies associated with EV, CES, PV, and the Grid

4. Use PSCAD to model high-frequency transients to assess the harmonic impact of multiple EV chargers on the electric network

5. Using actual system data to test the charging/discharging strategy

6. Calculate the five indices (Utilization factor, Capacity factor, Load factor, Power factor, and Power quality) for circuits 88—22 and 88-23

Changes in success criteria (Due to Demo design changes)

Equipment deployment in item (5) was reduced due the reduction in the anticipated EV penetration in Chatsworth. This impacted in the scope of test case of item (6)

Progress vs. success criteria

1. Develop models of Chatsworth using EDD – **Completed**

2. Test G2B, B2V, and B2G strategy using EDD model – **Completed**

3. Use mathematical modeling and analysis tool Matlab and Microsoft Excel to model and analyze various charging and discharging strategies associated with EV, CES, PV, and the Grid – **Completed**

4. Use PSCAD to model high-frequency transients to assess the harmonic impact of multiple EV chargers on the electric network – **Completed**

5. Demonstrate using actual system data to test the charging/discharging strategy – **Cannot be completed due to lack of data**

6. Calculate the five indices (Utilization factor, Capacity factor, Load factor, Power factor, and Power quality) for circuits 88—22 and 88-23 – **Completed**

Observations and Results

Observations and Results

- Some high-level observations are outlined below based on the EDD, MATLAB and PSCAD simulation studies:
    - Interaction of EVs, CES, and grid during the charging/discharging could have great impact on the power grid.
    - Based on the V2G and EV technology, allocation, the proportions of EVs, and centralized and decentralized interactive strategies are significantly important to impact on the grid. The key point of these strategies are managing peak load condition with EVs discharging to the grid to save electricity usage and shave the peak of the load curve.
    - It is suggested that commercialized EV benefits for the better future of developing EVs industry. Smart charging (G2V) for the purpose of "valley-filling" and V2G are very effective charging options compared to others.
    - The relationship between number of EV and power change is very linear. This can be used to predict the power needed when more EVs are in the system.
    - Reactive power will increase dramatically after the Battery Storage and EVs are plugged in, which will cause problems related to voltage stability in power grid.
    - Battery storage will generate higher harmonics when compared to no battery storage in the system which may damage the system and devices. However, the harmonics are much lower compared with PV system.

- The relationship between number of EV and the power change is very linear. This can be used to predict the power needed when more EVs are in the system.

- The harmonic test is largely based on how the models are built. Different EV models may also take us to different outcomes. Thus, all the conclusions in this paper can only be regarded as a reference. Practice is the sole criterion for testing truth.

Lessons Learned

- EDD program: There were great difficulties to learn and use the program due to the fact that the program is still is in its infancy and there is a lack of documentation and user base. Training by the software developer to LADWP and USC personnel was conducted initially to provide the necessary support. Furthermore, EDD was hired to help in the development of the model as well.
- Simulation Study: No actual data (1 year data) received to validate the results in the EDD, Matlab and PSCAD software, only simulation level of analysis is available for this use case.
- Observation based on the simulation studies is only possible at the present time. Equipment deployment, and about one-years of data collection will be required to conduct the actual system demonstrations.

Best Practices

NA

Results of Data Collection

Our analysis in Demo #8 was based on the ratings of the three power systems. The total capacity for each system using EDD is shown below:

IEEE 34 Bus Test System

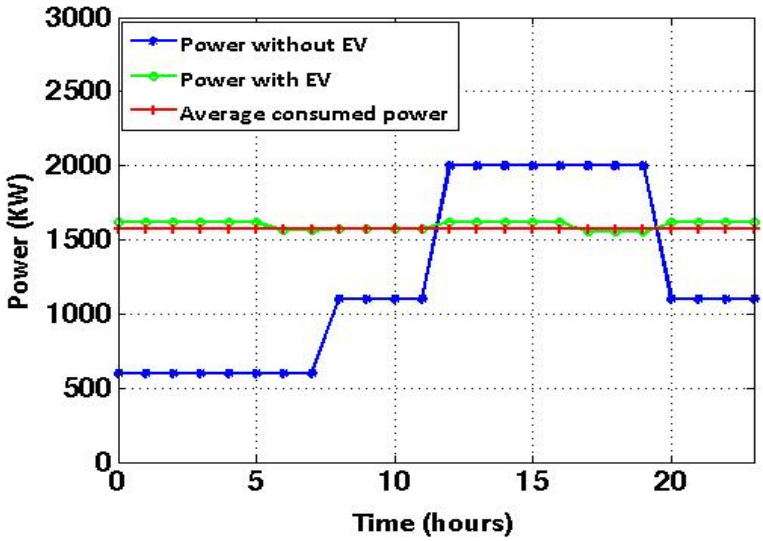
		EDD Result	**Standard**
Total Feeder Flow	kW	2043.17	2042.872
	kVAR	292.14	290.258
	kVA	2063.95	2063.389
Total Losses	kW	273.41	273.049
	kVAR	36.96	34.999
	kVA	275.90	275.283
Bus Current Flow	Ph-A	54.15	51.58
	Ph-B	46.81	44.57
	Ph-C	42.98	40.93

Chatsworth Distribution System Microgrid

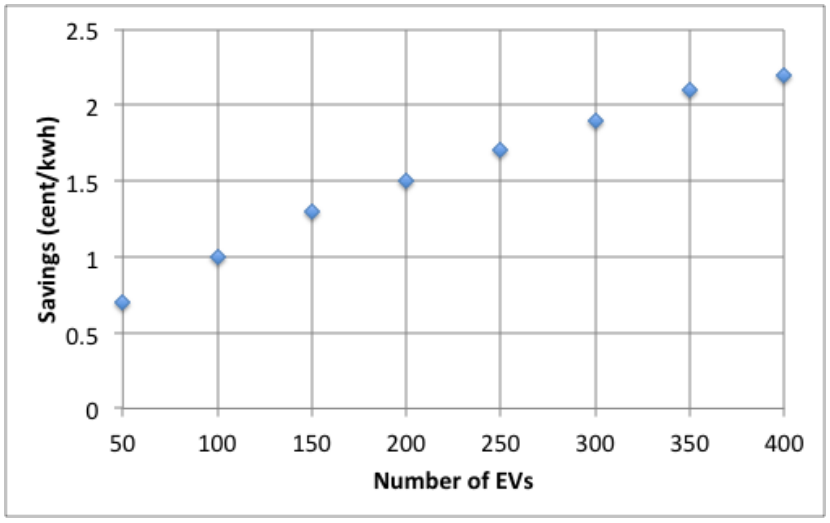
		EDD Result
Total Feeder Flow	MW	67.75
	MVAR	-6.175
	MVA	69.411
Total Losses	MW	0.889
	MVAR	2.562
	MVA	2.792

Data Collection Summary

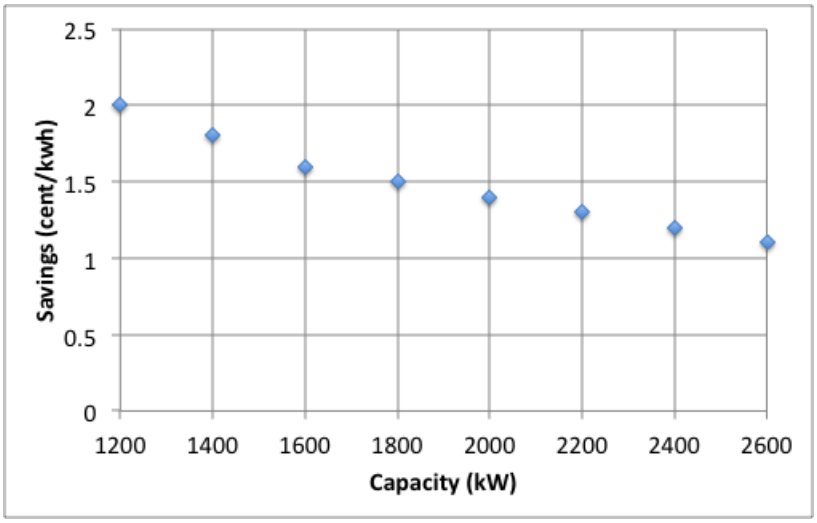
- Impact of battery aggregation and backfill strategies on IEEE34 system using MATLAB



- Economic savings for different number of electric vehicles added to the IEEE34 system



- Economic savings for different peak powers of the IEEE34 system



- Utilization factor for circuit 88-22

CASE 1	**Benchmark**		**Limit 1**		**Limit 2**	
	UF (reg)	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*
	0.551	0.134	1.97	0.478	3.75	0.911
CASE 2	**Benchmark**		**Limit 1**		**Limit 2**	
	UF (reg)	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*
	0.302	0.073	1.99	0.485	4.38	1.07
CASE 3	**Benchmark**		**Limit 1**		**Limit 2**	
	UF (reg)	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*
	0.164	0.04	1.85	0.45	4.85	1.18

- Power quality for circuit 88-22

	Peak	**Intermediate**	**Off-peak**
P (kW)	3937	4603.87	5093.18
Q (kVAR)	677.18	815.03	932.32
Worst Violation	109.6V	109.7V	109.2V
Δ Voltage (V)	10.4	10.3	10.8

- Utilization factor for circuit 88-23

Peak Loading Condition (100%)	**Benchmark**		**Limit 1**		**Limit 2**		**Limit 3**	
	UF (reg)	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*
	0.838	0.204	1.68	0.408	2.55	0.62	4.66	1.13
Intermediate Loading Condition (55%)	**Benchmark**		**Limit 1**		**Limit 2**		**Limit 3**	
	UF (reg)	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*
	0.452	0.11	1.67	0.406	N/A	N/A	5.53	1.34

Off-peak Loading Condition (30%)	Benchmark		Limit 1		Limit 2		Limit 3	
	UF (reg)	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*	*UF (reg)*	*UF (dis)*
	0.246	0.06	1.87	0.454	N/A	N/A	6.25	1.52

- Power quality for circuit 88-23

	Peak	Intermediate	Off-peak
P (kW)	4892.73	5809.72	6559.26
Q (kVAR)	868.97	1072.26	1263.21
Worst Violation	109.6V	109.7V	108.9V
Δ Voltage (V)	10.4	10.3	11.1

List of Reports Published under this Demo

- Deliverable Report #1 –Preliminary report data December 31, 2013
- Demo 8 Report – Progress Report date December 31, 2014

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established. Only simulations were planned.

Realized Impacts and Benefits to Date

None established. Only simulation results are available.

Disclaimers

The study results reported for Use Case 8 are based on the assumptions and data discussed in the report and are conducted using MATLAB, PSCAD and EDD analysis models. No thorough review has been done to assess the accuracy of the data or the analysis models for the purpose of this study and thus, USC doesn't warranty the accuracy or the use of these study results. The MATLAB, EDD and PSCAD power system analysis models are preparatory models supplied by

Appendix V Technology Performance Report (TPR) Use Case (Demonstration) #11

Technology Performance Report (TPR)
Use Case (Demonstration) #11
July 15, 2016

Demo/Use Case Name: Distribution Effects of EV's on the Grid

Brief Description:

This case demonstrates the interaction of EV(s), battery storage, and grid during the charging/discharging process. Ways are looked at to modify the daily load profile on the grid to take full advantage of the EV(s) and battery storage.

The fully functional Microgrid that was studied by the USC team included installed and operating EV chargers. The study analyzed the various positive and negative effects on the Microgrid such as: power quality issues (over-voltage, voltage sags, switching surges, harmonics and noise), impact on distribution infrastructure (transformers, wires, cables, and capacitors), capacity factor, utilization factor, load factor, system reliability, asset management, infrastructure optimization, cost effectiveness, and minimizing electric utility costs.

The requirements for demonstration #11 are listed as follows:

- Interaction of EV(s);
- Battery storage;
- Grid during the charging/discharging process

The USC EV research team tested various ways to modify the daily load profile on the grid to take full advantage of the EV(s) and battery storage.

Methodology

Assumptions

The demonstrations using a fully functional Microgrid provided the opportunity to both study larger grid impacts in a controlled environment and test the impacts of EVs on the future grid, which will likely include Microgrid technology. These demonstrations utilized data collected from LADWP Substations, Distribution Automation equipment, and AMI meters. Demonstration 11 dealt with Distribution Effects of EVs.

Demo responsibilities

The fully functional Microgrid that was studied by the USC team included the installed and operating EV chargers. The study analyzed the various positive and negative effects on the Microgrid such as: power quality issues (over-voltage, voltage sags, switching surges, harmonics and noise), impact on distribution infrastructure (transformers, wires, cables, and capacitors), capacity factor, utilization factor, load factor, system reliability, asset management, infrastructure optimization, cost effectiveness, and minimizing electric utility costs

One of the goals of the study was to demonstrate how customers can lower their demand charges or limit their daily electric loads with the EV chargers and battery storage. The USC team studied how to achieve the goal of load interruption during peak demands and load shifting of the EV chargers from daytime to nighttime whenever feasible. An energy management system was also studied that will capitalize on these new loads and energy storage.

This demonstration was completed at the SG Power Lab, the Various Demo Sites, and the SG EV Control Center. The main participants of this demonstration are LADWP and USC.

Demo steps and flow

1. Run Use Case #13 for more than 1 week to collect enough data to analyze and create process to control charging / discharging cycles
2. Review power consumption by time series (report each week during Use Case)
3. Review EV data by time series (report each week during Use Case)
4. Review any anomalies (Charging Stations or Battery errors) and report

Planned approach

1. Monitor and Evaluate Data from UCLA and LADWP
2. Document and report on distribution effects of EVs on the grid

Key changes in Demo design and justification

To meet the general system modeling and representation requirements outline in the design document, the following activities were undertaken by the USC EV research team:

1. Three sets of distribution network models were selected to enable analysis of EV distribution effects as described in the SGRDP Preliminary Design Document.
    a. An IEEE 34 bus test system reflecting an industry standard distribution test model
    b. A USC distribution network or microgrid reflecting a large urban complex in the LADWP system
    c. A Chatsworth Distribution System or microgrid representing a residential/industrial area in the LADWP system with a special focus to the circuit numbers 22 and 23
2. Four software programs were selected for the development of these models. These software programs are:
    a. Distribution system modeling software Distribution Engineering Workstation (DEW) by Electrical Distribution Design, Inc. (EDD) was used to model the distribution network
    b. Power system distribution simulator software OpenDSS by Electric Power Research Institute (EPRI) was used to model the distribution networks
    c. Designing distributed generation (DG) systems software HOMER by National Renewable Energy Laboratory was used to evaluate the economic and technical feasibility of a large number of technology options and to account for variations in technology costs and energy resource availability
    d. A multi-paradigm numerical computing environment and fourth-generation programming software MATLAB by Mathworks was used to develop an Utility-Customer Interface Strategy and User Application for Electric Vehicles and Distributed Generation Management

3. The EDD models on the three system representations (IEEE 34 bus, USC, and Chatsworth) and OpenDSS models on the two system representations (IEEE 34 bus and USC) allowed the attachment of multiple EV-charger loads of various classifications
4. The EDD models on the three system representations (IEEE 34 bus, USC, and Chatsworth) and OpenDSS models on the two system representations (IEEE 34 bus and USC) were designed to reveal the aggregate effect of the multiple EV-charger loads at substation connections to the transmission grid
5. A utility - customer interface strategy and user application for electric vehicles and distributed generation management was created achieve the goal of load interruption during peak demands and load shifting of the EV chargers from daytime to nighttime whenever feasible

Technologies Deployed

List of systems/equipment deployment

Three sets of distribution network models were selected to enable analysis of EV distribution effects as described in the SGRDP Preliminary Design Document.

a) An IEEE 34 bus test system reflecting an industry standard distribution test model
b) A USC distribution network or microgrid reflecting a large urban complex in the LADWP system
c) A Chatsworth Distribution System or microgrid representing a residential/industrial area in the LADWP system with a special focus to the circuit numbers 22 and 23

Software and Models Summary

- EDD: IEEE 34, USC, Chatsworth
- OpenDSS: IEEE 34, USC
- HOMER: USC Microgrid design and operation
- MATLAB: Utility-Customer Interface and user application for EV and DG management

Success Criteria

Description of success criteria for this Demo

1. Develop models of Chatsworth (as well as IEEE and USC) using EDD (as well as OpenDSS, and HOMER)
2. Test the interaction of EV(s), battery storage, and grid during the charging / discharging process using EDD model
3. Test USC microgrids using OpenDSS model
4. Deploy/Install specified equipment
5. Demonstrate the interaction of EV(s), battery storage, and grid during the charging / discharging process
6. Deploy an utility - customer interface strategy and user application for electric vehicles and distributed generation management
7. Demonstrate actual Chatsworth microgrid

Changes in success criteria

- Equipment deployment in item (4) was greatly reduced due to the reduction in the anticipated EV penetration in Chatsworth. This will impact in the scope of test case of item (4)

- Demonstration item (7) was not done since microgrid applications that required facility enhancements were not implemented for the Chatsworth system.

Progress vs. success criteria

1. Develop models of Chatsworth (as well as IEEE and USC) using EDD (as well as OpenDSS, and HOMER) **- Completed**
2. Test the interaction of EV(s), battery storage, and grid during the charging / discharging process using EDD model **- Completed**
3. Test USC microgrids using PSS/E model **- Completed**
4. Deploy/Install specified equipment **– Not Done**
5. Demonstrate the interaction of EV(s), battery storage, and grid during the charging / discharging process **– Completed**
6. Deploy an utility - customer interface strategy and user application for electric vehicles and distributed generation management **– Completed**
7. Demonstrate actual Chatsworth microgrid **– Not Done**

Observations and Results

Preliminary Observations and Results

- Observation based on the simulation studies is only possible at the present time. Equipment deployment, and about one-years of data collection will be required to conduct the actual system demonstrations.
- Modeling of the Chatsworth (as well as the IEEE and USC test systems) using EDD (as well as PSS/E) is done successfully.
- Testing of the Chatsworth (as well as the IEEE and USC test systems) using EDD (as well as PSS/E, and HOMER) is done successfully.

Lessons Learned

- EDD program; There were great difficulties to learn and use the program due to the fact that the program is still is in its infancy and there is a lack of documentation and user base. Training by the software developer to LADWP and USC personnel was conducted initially to provide the necessary support. Furthermore, EDD was hired to help in the development of the model as well.
- Simulation Study: No actual data (1 year data) received to validate the results in the EDD, OpenDSS software, only simulation level of analysis is available for this use case. OpenDSS results were used to compare with the analysis done by EDD, same scenarios were tested and verified in OpenDSS.

Conclusions

The cost of the microgrid on "islanded mode" is much larger than the cost when the grid is considered as an energy supply. The fuel cost of the microturbines, natural gas, is very expensive compared to the cost of energy provided by the utility LADWP which is almost 17 cents. Micro turbines have very low capital cost but a very high fuel cost which represent by far the biggest share in each scenario and their lifetime is almost 2 straight years or (15000 Hours), during each scenario, they have to be replaced 10 times in average , which makes the cost even larger. PV panels have the highest capital cost; however, solar panels life time is 25 years, much longer than microturbines. Salvage equipment sale is almost 10 % of original prices.

On the other side, the grid-connected mode scenarios have nearly similar net present costs but the differences come when considering the amount of GHG and other emissions accompanied each scenario as well as the additional reliability and security to the university demand.

The existing system (with no microgrid) is economically the most optimal than the suggested microgrid. The net present cost of the existing system (LADWP) is 42.7 Million. The net present cost of the microgrid with (2.5 MW PV, 500 KWh batteries, and 2 MW Microturbines) is slightly higher at 46 Million. However, regardless of the cost, the microgrid will add reliability and security to the campus electrical demand. The advantages of the microgrid on an environmental level and security regard make the cost difference even more ignorable.

In this research, the critical load of USC Microgrid has been identified and a list of critical buildings has been provided. In addition, an optimization process has been conduct to find the most optimal microgrid plan using the best available energy resources. The most optimal option has come up to be a combination of microturbines, PVS, batteries, inverters, and the main grid (LADWP).

Best Practices

None established.

Results of Data Collection

There is no significant level of data to assess at the present time.

Data Collection Summary

Large amount of system data has been collected associated with this Use Case. This data is available in the USC data server for analysis. A list of the system conditions that were studied and data was collected and analyzed is given below:

- CASE 1.1: Random Charging at period 1 (100% Load Condition)
- CASE 1.2: Random Charging at period 2 (55% Load Condition)
- CASE 1.3: Random Charging at period 3 (30% Load Condition)
- CASE 2.1: 10% Load Continuous Increment in Order at period 1
- CASE 2.2: 10% Load Continuous Increment in Order at period 2
- CASE 2.3: 10% Load Continuous Increment in Order at period 3
- CASE 3.1: 10% Increment Each Time of all the Load at period 1
- CASE 3.2: 15% Increment Each Time of all the Load at period 2
- CASE 3.3: 20% Increment Each Time of all the Load at period 3

- Three system representation were as outlined below:
  - An IEEE 34 bus test system reflecting an industry standard distribution test model
  - A USC distribution network or microgrid reflecting a large urban complex in the LADWP system
  - A Chatsworth Distribution System or microgrid representing a residential/industrial area in the LADWP system with a special focus to the circuit numbers 22 and 23

List of Reports Published under this Demo

- Deliverable Report #2 –Preliminary report data March 31, 2014

- Demo 11 Report – Progress Report date December 31, 2014
- Impact of Electric Vehicle Infrastructure on the City of Chatsworth Distribution System - IEEE International Electric Vehicle Conference 2014
- Impact of Electric Vehicles on the IEEE 34 Node Distribution Infrastructure - 2014 International Conference on Smart Grid and Clean Energy Technologies
- Impact of EV Infrastructure on the University of Southern California Microgrid - The 3rd International Conference on Connected Vehicles and Expo
- Utility-Customer Interface Strategy and User Application for Electric Vehicles and Distributed Generation Management – Master Thesis April 2016
- USC Microgrid Development Conceptual Plan - Master Thesis April 2014

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established. Only simulations were planned.

Realized Impacts and Benefits to Date

None established. Only simulation results are available.

Disclaimers

The study results reported for Use Case 11 are based on the assumptions and data discussed in the report and are conducted using EDD and OpenDSS analysis models. No through review has been done to assess the accuracy of the data or the analysis models for the purpose of this study and thus, USC doesn't warranty the accuracy or the use of these study results. The EDD and OpenDSS power system analysis models are preparatory models supplied by the respective venders.

Appendix W Technology Performance Report (TPR) Use Case (Demonstration) #18

Technology Performance Report (TPR)
Use Case (Demonstration) #18
July 15, 2016

Demo/Use Case Name: Monitoring of Chargers, Power Usage, and Car Usage

Brief Description:

In this use case, a study was done on charging station and Electric Vehicle (EV) usage in Los Angeles, CA. The data was classified into three major categories: large corporate fleet, local residential EV and LADWP ride share EV. The usage of EV and charging stations, as well as the charging patterns, were recorded and analyzed for a time period of one year. The EV usage data and station records came from two sources: Los Angeles Department of Water and Power (LADWP) and University of California, Los Angeles (UCLA). LADWP data together with UCLA data will be used to represent large corporate fleet. The results was used to provide information and practical insights for LADWP and other similar utility companies for resource planning and future installations of wired and wireless charging infrastructures for EV.

Design Document Methodology (anticipated in 2011)

Assumptions

The Car/Ride Share Center utilized the LADWP's car fleet that is designed to be used for day to day activities by personnel. The existing EV charging infrastructure was retrofitted to accommodate the new EV's charging standards. More than fifty EV cars from major manufacturers were purchased to be utilized in the fleet. The fleet was used to demonstrate the Distribution Effects of the EV Car/Ride Share program, and the various Smart Charging demonstrations. In addition, EV charging start time, duration, energy and other charging information was collected from each charging station on daily basis for analysis purposes.

This program consisted of adding EVs to the existing fleet of LADWP cars. Along with the vehicles, additional parking spaces and signage was allocated in different LADWP locations depending on the determined need.

Demo responsibilities

EV charging data was collected either through meters or through a third party (FleetCarma). Power consumption data was stored using timestamp information. In addition, the miles driven between each charging session was collected for statistical analysis and EV driving characterization. Once enough power consumption data was collected to determine usage patterns and load curve shapes, analysis was performed to investigate the feasibility of using EV chargers to levelize the load curve by removing/reducing peaks and valleys. Another benefit of charger monitoring was the ability to detect a charger failure in timely manner.

There were three types of EV stations that were monitored by this demonstration:

1. One was for the use in the **LADWP Fleet**, and these EVs were used by employees for daily operations. These cars were distinguished by short-range, frequent usage during working hours.

2. Another station was for **local public use**. These cars were allotted to the public for part of the work day. This scenario was distinguished by very short-range and infrequent use relative to the previously described station.
3. A third station was used by **LADWP employees for Ride Share** use. This situation was distinguished by longer range, daily usage. These vehicles also were left overnight without charging, so the battery depletion per ride should be significantly larger than the other two scenarios.

Demo steps and flow

1. Collect data (including also Use Case #2) for more than 1 year to collect enough data to analyze and report results
2. Review power consumption by time series (report each quarter)
3. If available, review EV data by time series (report each quarter)
4. Review any anomalies (Charging Stations or BMS errors) and report

Planned approach (as approved by DoE)

1. Monitor and Evaluate Data from Ride Share Program
2. Document and report on Ride Share Program

Final Used Methodology

Key changes in Demo design and justification

There were some deviations to the three types of EV stations that were monitored by this demonstration. They included:

- Data will come from UCLA and LADWP to reflect the charging station usage for large corporate-university use to provide a bigger data pool. The data collection included a range of operational use cases and conditions, charging stations, corporation fleet and personal EVs.
- No data was collected for the charging stations of local public use because there was no capability to do so at the time. Instead, data of EV charging in the residential areas within LADWP EV rebate program were collected from February 1st to April 30th 2016.

Based on the above changes, the demonstration is divided into three tasks:

A. Charging Station Usage, Power Usage and Car Usage of large corporate fleet:
   1. LADWP assigned EVs
   2. UCLA EV fleet
B. Charging Station Usage, Power Usage and Car Usage in LADWP local residential area
C. Charging Station Usage, Power Usage and Car Usage of LADWP ride share

Task A1: To meet the general system modeling and representation requirements of design document for the LADWP charging station usage, power usage and car usage of 36 assigned EVs, the following activities were under taken by the USC EV research team:

1. LADWP assigned EV fleet and charger overview
2. Charging patterns of all assigned EVs in LADWP from May 2015 to May 2016
3. Charging station usage and power usage in LADWP for assigned EVs from May 2015 to May 2016
   a. Hourly
   b. Weekday vs. weekend
   c. Seasonally

    d. One year
4. Load curve prediction in California using LADWP assigned EV data

Task A2: To meet the general system modeling and representation requirements of design document for the UCLA charging station usage, power usage and car usage, the following activities were under taken by the USC EV research team:

1. UCLA fleet and charger overview
2. Charging patterns of all EVs in LADWP from July 2014 to August 2015
3. Charging station usage and power usage in LADWP from July 2014 to June 2015
    a. Hourly
    b. Weekday vs. weekend
    c. Seasonally
    d. One year
4. Load curve prediction in California using UCLA data

Task B: To meet the general system modeling and representation requirements of design document for the LADWP residential charging station usage, power usage and car usage, the following activities were under taken by the USC EV research team:

1. LADWP residential charger overview
2. Charging patterns of all residential EVs in LADWP service territory from February 1st to April 30th 2016
3. Charging station usage and power usage in LADWP for residential EVs within LADWP service territory from February 1st to April 30th 2016
    a. Hourly
    b. Weekday vs. weekend
    c. Seasonally

Task C: To meet the general system modeling and representation requirements of design document for the LADWP charging station usage, power usage and car usage of 30 carpool EVs, the following activities were under taken by the USC EV research team:

1. LADWP ride share fleet and charger overview
2. Charging patterns of all carpool EVs in LADWP from May 2015 to May 2016
3. Charging station usage and power usage in LADWP for carpool EVs from May 2015 to May 2016
    a. Hourly
    b. Weekday vs. weekend
    c. Seasonally
    d. One year
4. Load curve prediction in California using LADWP carpool data

Technologies Deployed

List of systems/equipment deployment

- AMI Meters Customer (Residential, C&I, EV)
- More than 1000 EV Chargers
- FleetCarma
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification**"

Progress vs. success criteria

Task A1: Charging Station Usage, Power Usage and Car Usage of large corporate fleet:

1. LADWP assigned EV fleet and charger overview - **Completed**
2. Charging patterns of all assigned EVs in LADWP from May 2015 to May 2016 - **Completed**
3. Charging station usage and power usage in LADWP for assigned EVs from May 2015 to May 2016 - **Completed**
    a. Hourly
    b. Weekday vs. weekend
    c. Seasonally
    d. One year
4. Load curve prediction in California using LADWP assigned EV data - **Completed**

Task A2: Charging Station Usage, Power Usage and Car Usage of large corporate fleet:

1. UCLA fleet and charger overview - **Completed**
2. Charging patterns of all EVs in LADWP from July 2014 to August 2015 - **Completed**
3. Charging station usage and power usage in LADWP from July 2014 to June 2015 - **Completed**
    a. Hourly
    b. Weekday vs. weekend
    c. Seasonally
    d. One year
4. Load curve prediction in California using UCLA data - **Completed**

Task B: Charging Station Usage, Power Usage and Car Usage in LADWP local residential area

1. LADWP residential charger overview - **Completed**
2. Charging patterns of all residential EVs in LADWP service territory from February 1st to April 30th 2016 - **Completed**
3. Charging station usage and power usage in LADWP for residential EVs within LADWP service territory from February 1st to April 30th 2016 - **Completed**
    a. Hourly
    b. Weekday vs. weekend
    c. Seasonally

Task C: Charging Station Usage, Power Usage and Car Usage of LADWP ride share

1. LADWP ride share fleet and charger overview - **Completed**
2. Charging patterns of all carpool EVs in LADWP from May 2015 to May 2016 - **Completed**
3. Charging station usage and power usage in LADWP for carpool EVs from May 2015 to May 2016 - **Completed**
    a. Hourly
    b. Weekday vs. weekend
    c. Seasonally
    d. One year
4. Load curve prediction in California using LADWP carpool data - **Completed**

Observations and Results

Observations and Results

1. Large Corporate Fleet and Associated Charging Stations

1.1 LADWP Fleet and Charging Station

36 EVs on 5 brands and 8 models, and multiple chargers at level 1, 2 and 3 were selected and tested in LADWP. EV charging events were recorded from May 20th, 2015 to May 20th, 2016. Energy transferred for all 3,073 charging events were studied and the plug-in time per charging were examined. As for charging station usage, 24 hour energy distribution were plotted and analyzed daily, monthly, seasonally, and yearly. The statistic results were used to provide information and practical insights for utility companies to make city planning and future installations of the EV charging infrastructures.

The result from EV charging events implement that 90% of charging events transferred less than 11 kWh. Regarding the EV plug-in time, 94% of the time EV was connected for less than 4 hours, while less than 1% of the time EV users plugged in their EVs for more than 5 hours.

From the charging station usage, the USC EV team concluded that it is possible to use EV chargers to levelize load curve shapes by removing or reducing peaks and valleys. Two energy peaks brought by EV charging from the grid were between 7-8am and 1-3 pm, respectively. The 24 hour charging energy distribution curve is similar to the daily load curve in California. Charging stations delivered most of the energy to all EVs during daytime, which could be offset by installing PV panels.

1.2 UCLA Fleet and Charging Station

More than 17 EVs and 19 chargers at level 1, 2 and 3 were selected and tested in UCLA campus. EV charging events were recorded from June 1st, 2014 to August 31st, 2015 while charging station data were collected every 15 minutes since July 1st, 2014. Energy transferred for all 19,617 charging events were studied and the plug-in time per charging were examined. As for charging station usage, 24 hour energy distribution were plotted and analyzed hourly, daily, monthly, quarterly, and yearly. The statistic results were used to provide information and practical insights for utility companies to make city planning and future installations of the EV charging infrastructures.

The result from EV charging events showed that 90% of charging events transferred less than 12 kWh. Regarding the EV plug-in time, 67% of the time EV was connected for less than 4 hours, while 87% of the time EV users plugged in their EVs for less than 7 hours.

From the charging station usage, the USC EV team concluded that it is possible to use EV chargers to levelize load curve shapes by removing or reducing peaks and valleys. Energy peak brought by EV charging from the grid was between 7-10am when EV users came to work. The 24 hour charging energy distribution curve is similar to the daily load curve in California only except the EV charging peak time occurred in the morning. Charging stations delivered most of the energy to all EVs during daytime, which could be offset by installing PV panels.

2. Residential EV and Associated Charging Stations

In the residential areas within the LADWP service territory, 223 EV rebate meter data were collected and analyzed to represent for local public use of EV. Each meter reflected information of one home and recorded 240V level 2 EV charging energy. The data used in this analysis was from February 1st 2016 to April 30th 2016. All meters recorded and updated the chargers' information every 15 minutes. The pilot data collected from these 223 rebate meters included more than 1 million records of EV charging.

From the charging station usage, the USC EV team concluded that it is possible to use EV chargers to levelize load curve shapes by removing or reducing peaks and valleys. Energy peak brought by EV charging from the grid was between 8-10 pm. The 24 hour charging energy distribution curve is pretty desirable to the utility company because there was small amounts of energy used in the daytime while large amounts were used in the evening. It would be better if the utility companies applied V2G technology to direct the EV customers to start charging in the middle of night to increase the off-peak demand and help optimize the actual daily load curve.

3. LADWP Ride Share EV and Associated Charging Stations

30 EVs on 2 brands and 2 models, and multiple chargers at level 1, 2 and 3 were selected and tested in LADWP. EV charging events were recorded from May 20th, 2015 to May 20th, 2016. Energy transferred for all 8,211 charging events were studied and the plug-in time per charging were examined. As for charging station usage, 24 hour energy distribution were plotted and analyzed daily, monthly, seasonally, and yearly. The statistic results were used to provide information and practical insights for utility companies to make city planning and future installations of the EV charging infrastructures.

The result from EV charging events showed that 90% of charging events transferred less than 8.77 kWh. Regarding the EV plug-in time, 84% of the time EV was connected for less than 2 hours, while less than 1% of the time EV users plugged in their EVs for more than 5 hours.

From the charging station usage, the USC EV team concluded that it is possible to use EV chargers to levelize load curve shapes by removing or reducing peaks and valleys. Energy peak brought by EV charging from the grid was between 3-4 pm. The 24 hour charging energy distribution curve is pretty similar to the daily load curve in California. Charging stations delivered most of the energy during daytime, which could be offset by installing PV panels.

Lessons Learned

- FleetCarma; Initial attempts to internally develop data monitoring and collection tools were not successful and. Having a commercially available collection system like FleetCarma for was very helpful.
- There were difficulties to lean and use the data provided by FleetCarma due to the lack of certain information for direct analysis. Macros and algorithms were created in Microsoft Excel to replicate all data and plots on FleetCarma before process the data. In the future it would be desirable to have good documentation and vendor support to avoid the above mentioned issues.
- Data from UCLA; There were some discrepancy of the data format provided by UCLA. Data is only available from July 2014 to August 2015, no further data has been provided after that.
- Data of EV charging in LADWP local residential area were only collected from February 1st to April 30th 2016. The analysis may not correctly reflect the whole year charging usage of local residential EVs.

Best Practices

None established.

Results of Data Collection

- Large amount of data has been collected associated with this Use Case. This data is available in the USC data server for analysis. Some sample data analysis results are for each of the Tasks is given in the following section.

Data Collection Summary (Graphs, Table, etc…)

1. Large Corporate Fleet and Associated Charging Stations

1.1 LADWP Fleet and Charging Station

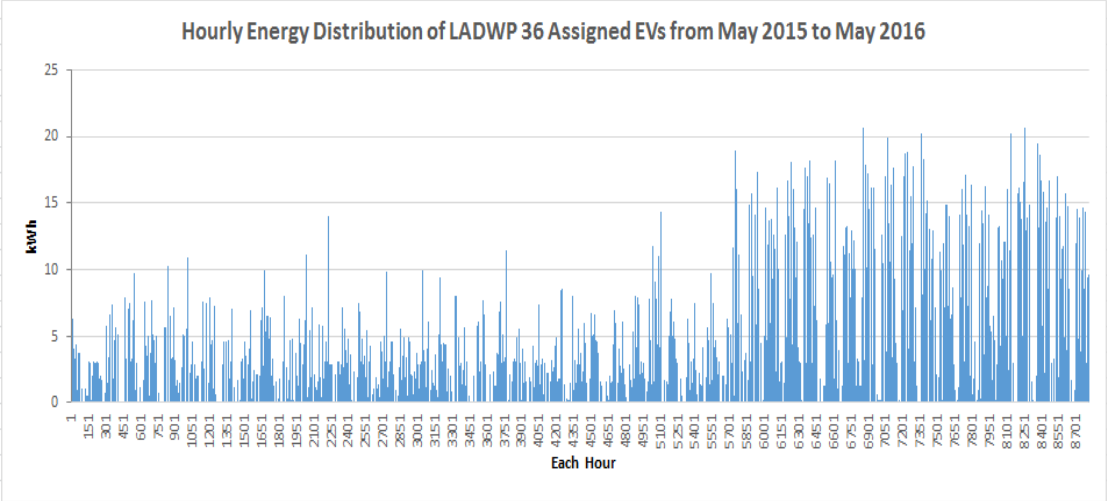


Figure 1 Hourly Charging Distribution of LADWP 36 Assigned EVs, May 2015 to May 2016

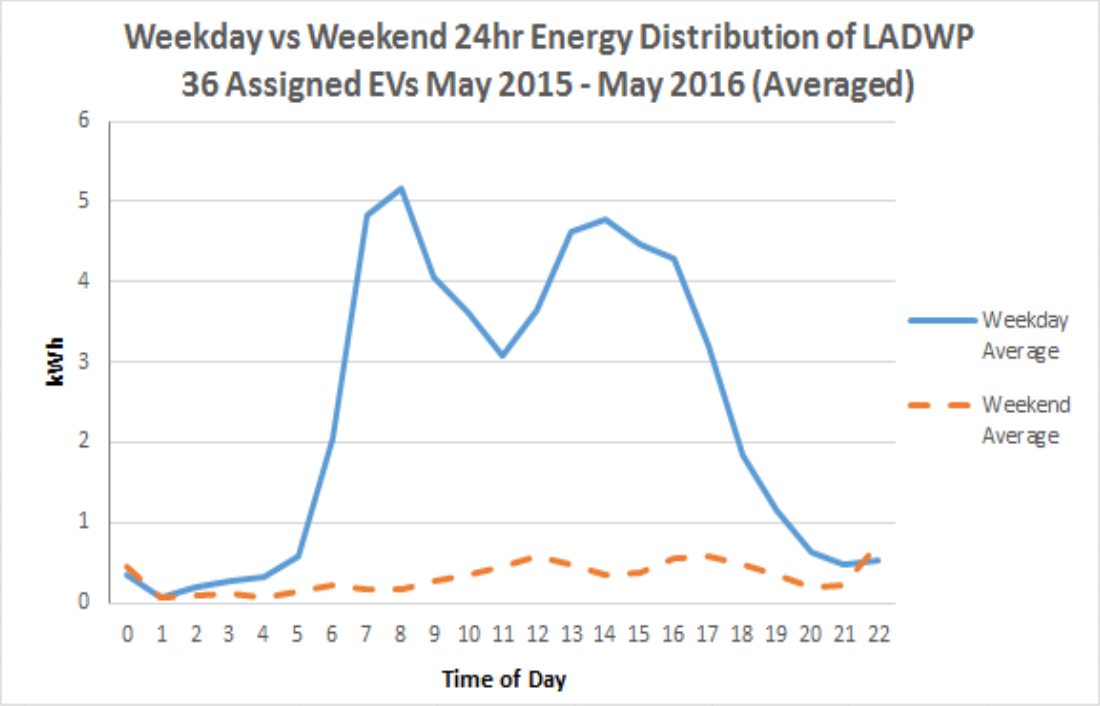


Figure 2 Comparison of Averaged Weekday and Weekend 24 hour Energy Distribution of LADWP 36 Assigned EVs from May 2015 to May 2016

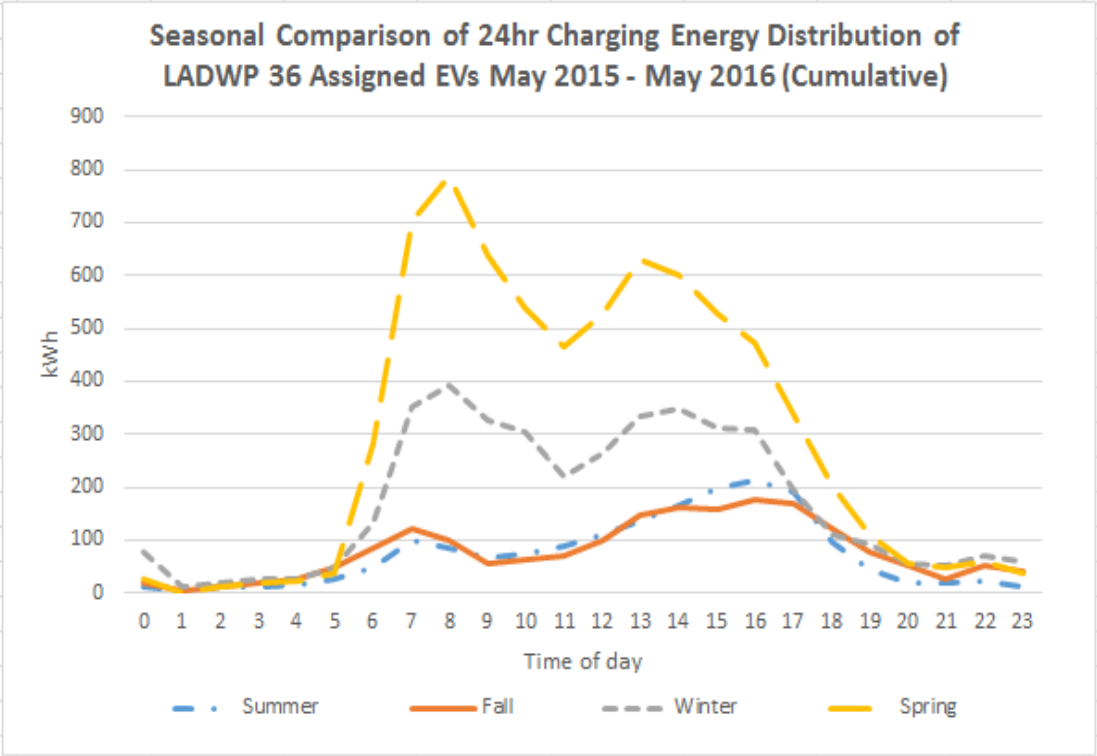


Figure 3 Seasonal Comparison of 24 Hour Cumulative Charging Energy Distribution of LADWP 36 Assigned EVs from May 2015 to May 2016

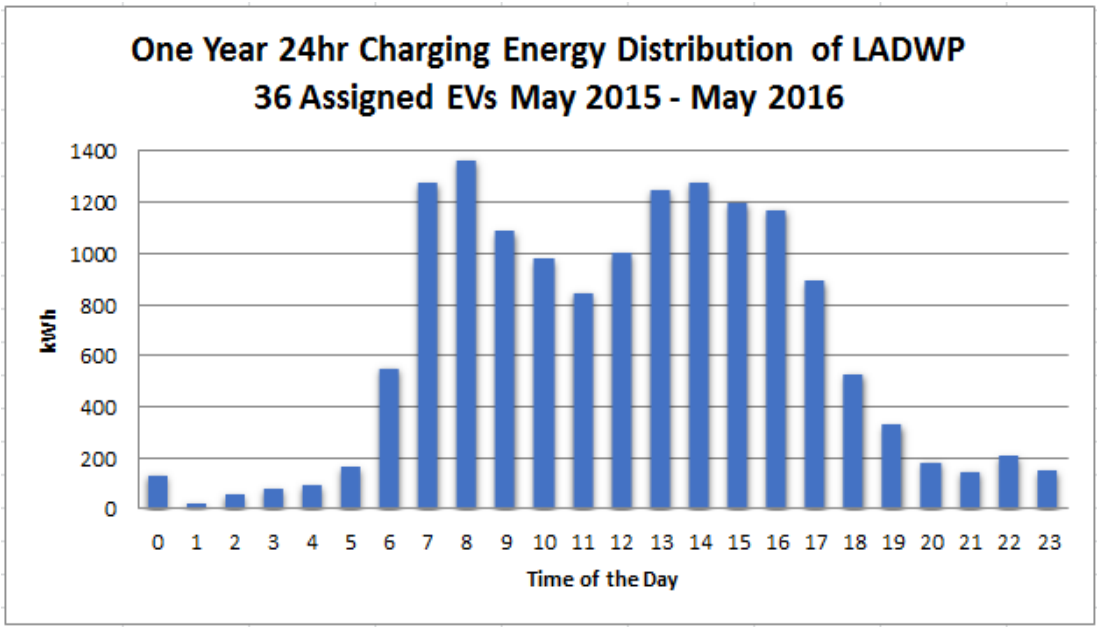


Figure 4 One Year Cumulative 24 hour Energy Distribution of LADWP 36 Assigned EVs from May 2015 to May 2016

1.2 UCLA Fleet and Charging Station

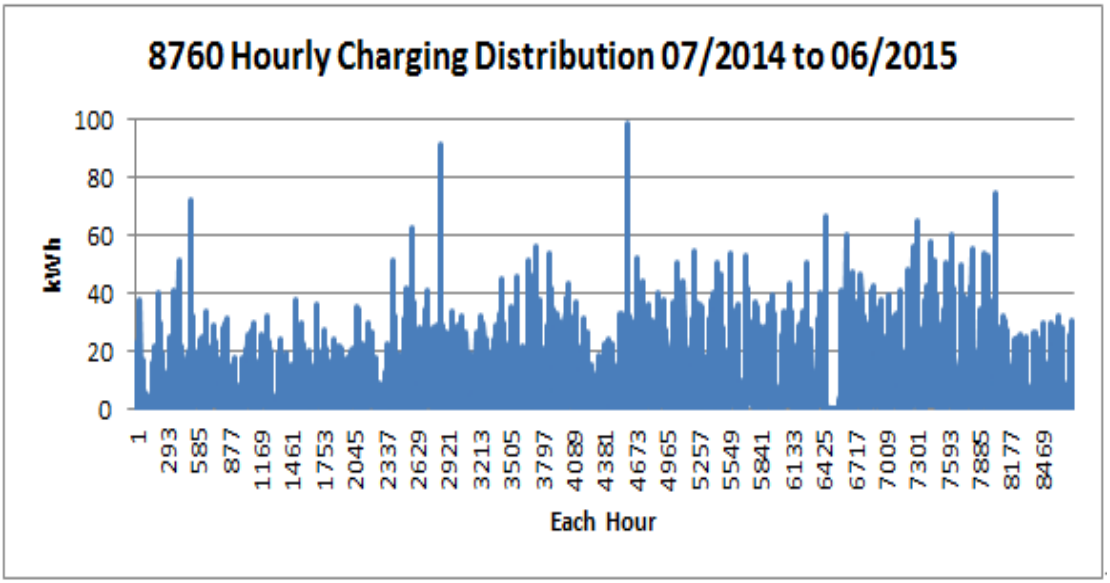


Figure 5 8760 Hourly Charging Distribution in UCLA from July 2014 to June 2015

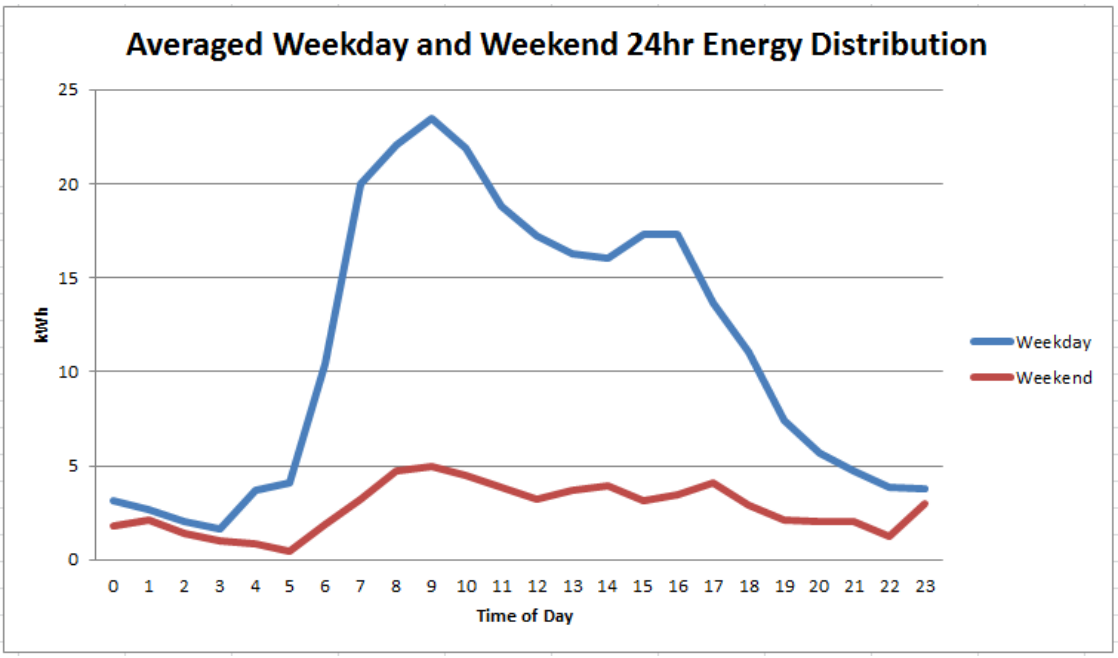


Figure 6 Comparison of Averaged Weekday and Weekend 24 hour Energy Distribution in UCLA from July 2014 to June 2015

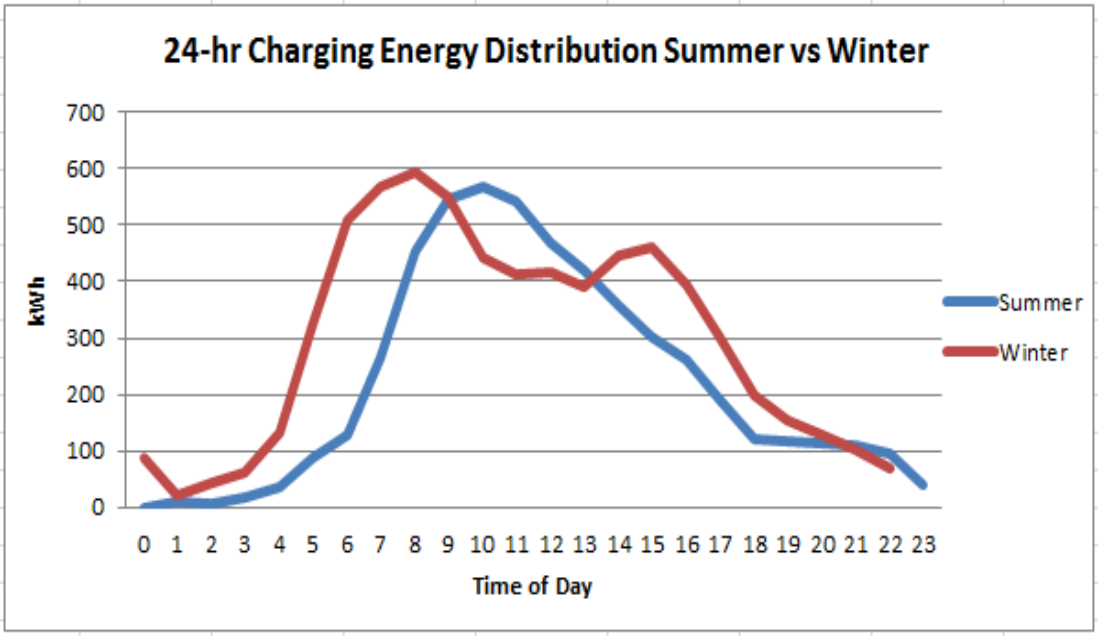


Figure 7 Comparison of Winter 2014 and Summer 2015's Cumulative Charging Energy Distribution in UCLA

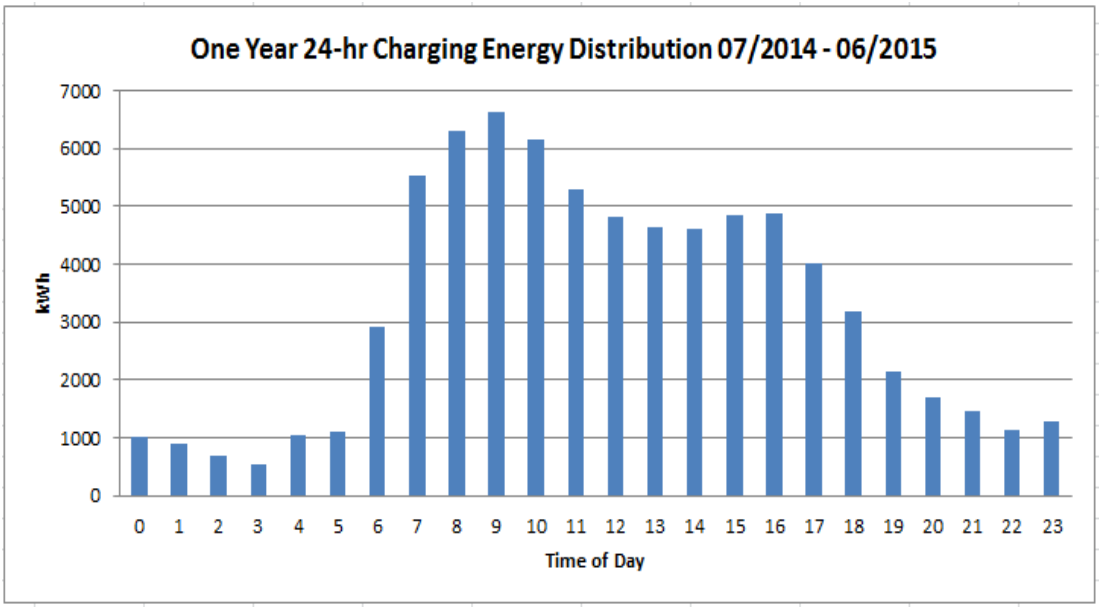


Figure 8 One year Cumulative 24 hour Energy Distribution in UCLA from July 2014 to June 2015

2. Residential EV and Associated Charging Stations

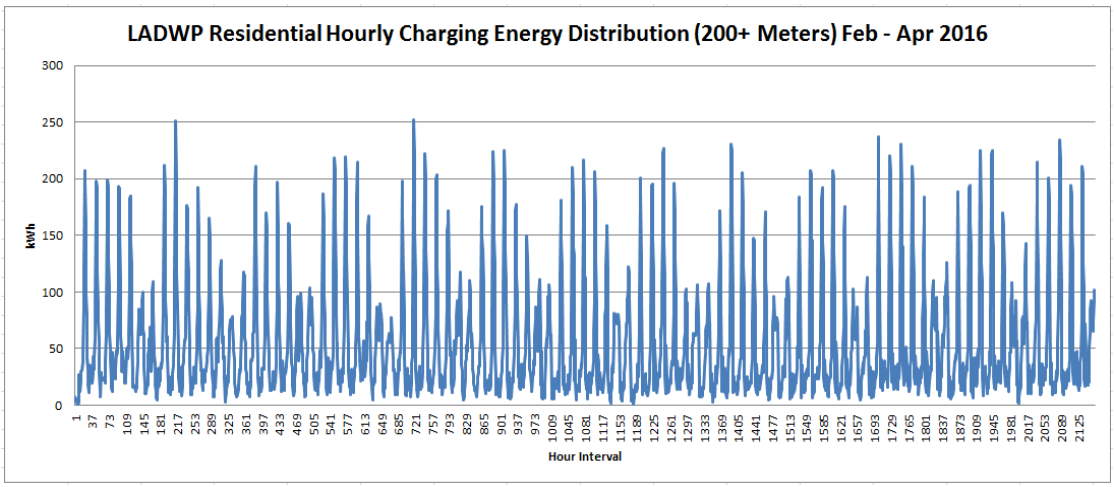


Figure 9 Hourly Charging Distribution in LADWP Residential Area, February to April 2016

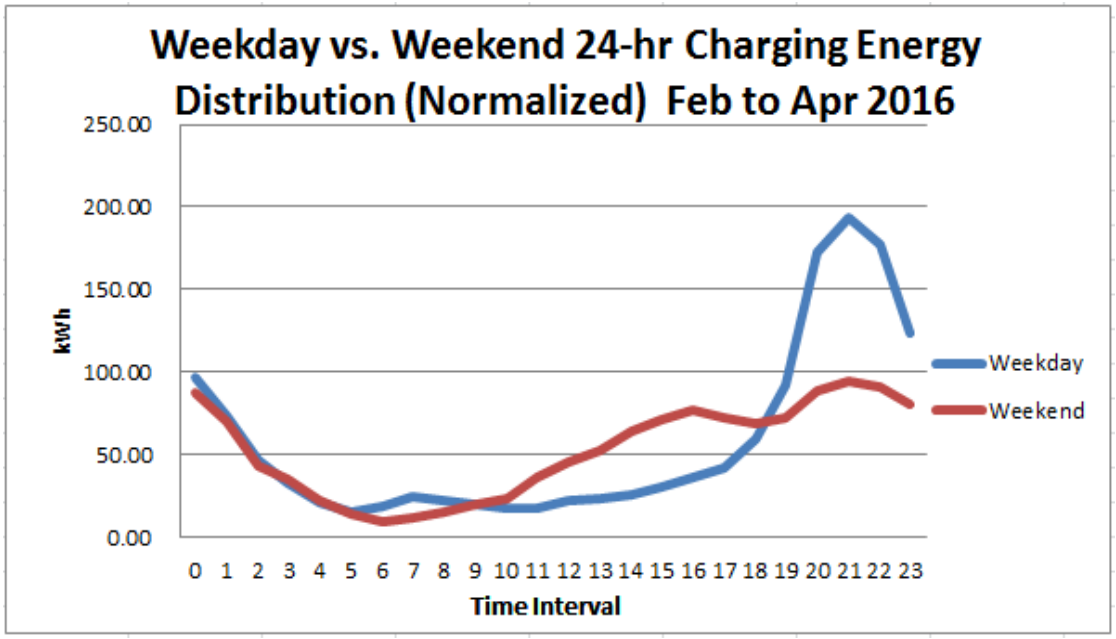


Figure 10 Comparison of Normalized Weekday and Weekend 24 hour Energy Distribution in LADWP Residential Area, February to April 2016

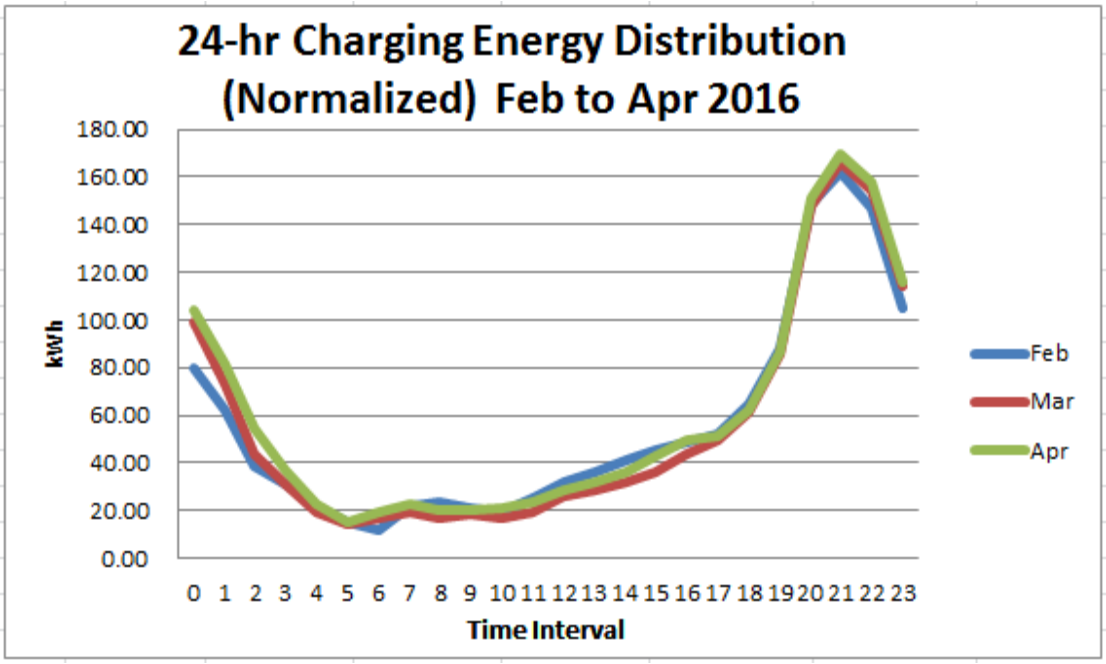


Figure 11 Monthly Comparison of 24 Hour Cumulative Charging Energy Distribution in LADWP Residential Area, February to April 2016

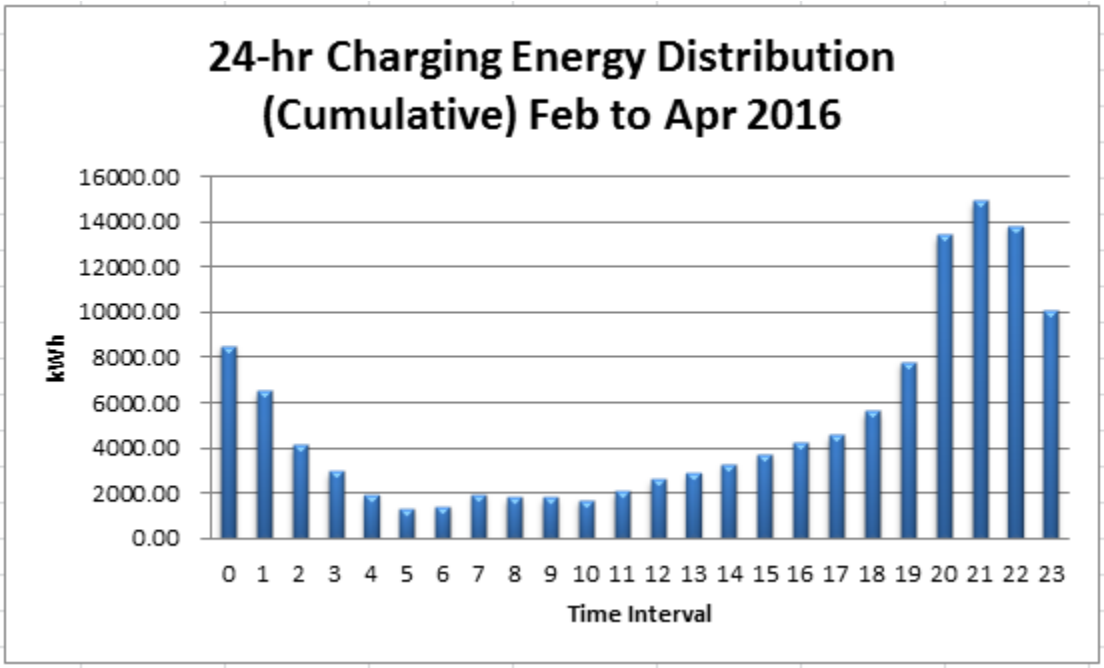


Figure 12 Cumulative 24 hour Energy Distribution in LADWP Residential Area, February to April 2016

3. LADWP Ride Share EV and Associated Charging Stations

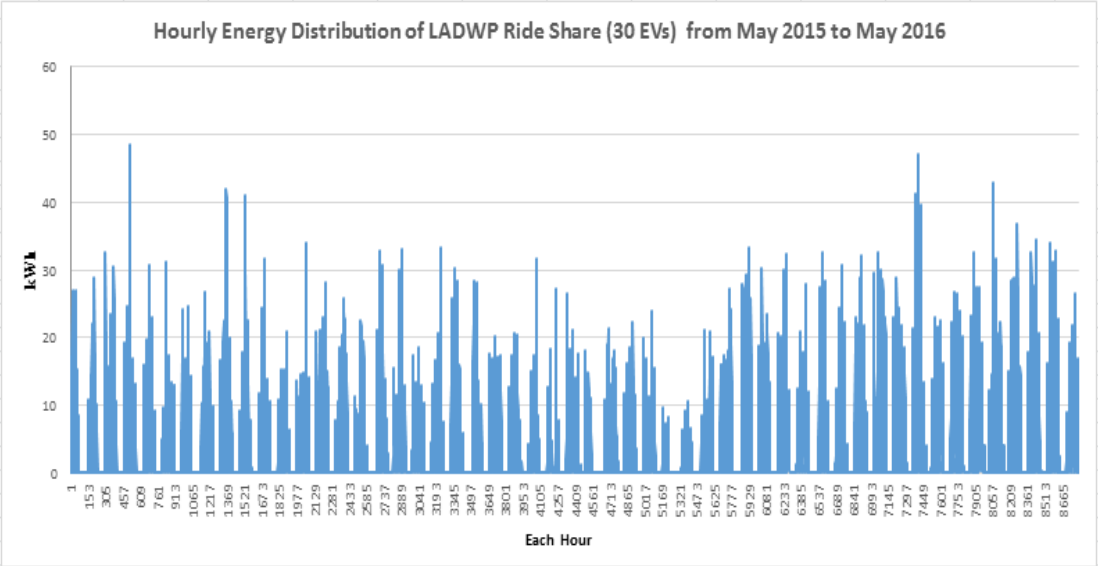


Figure 13 8808 Hourly Charging Distribution of LADWP Ride Share (30 EVs) May 2015 to May 2016

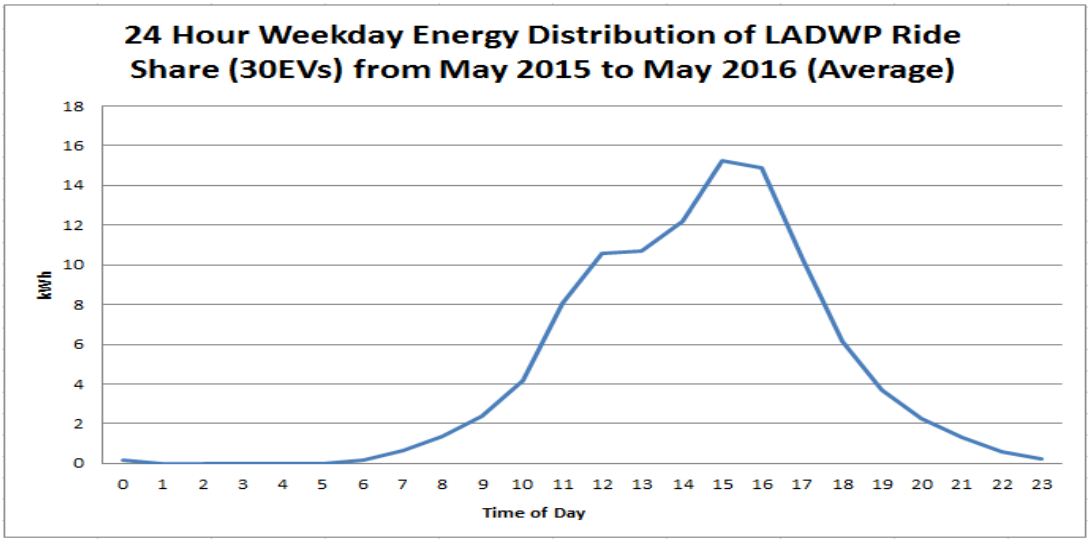


Figure 14 Averaged Weekday 24 hour Energy Distribution of LADWP Ride Share (30 EVs) May 2015 to May 2016

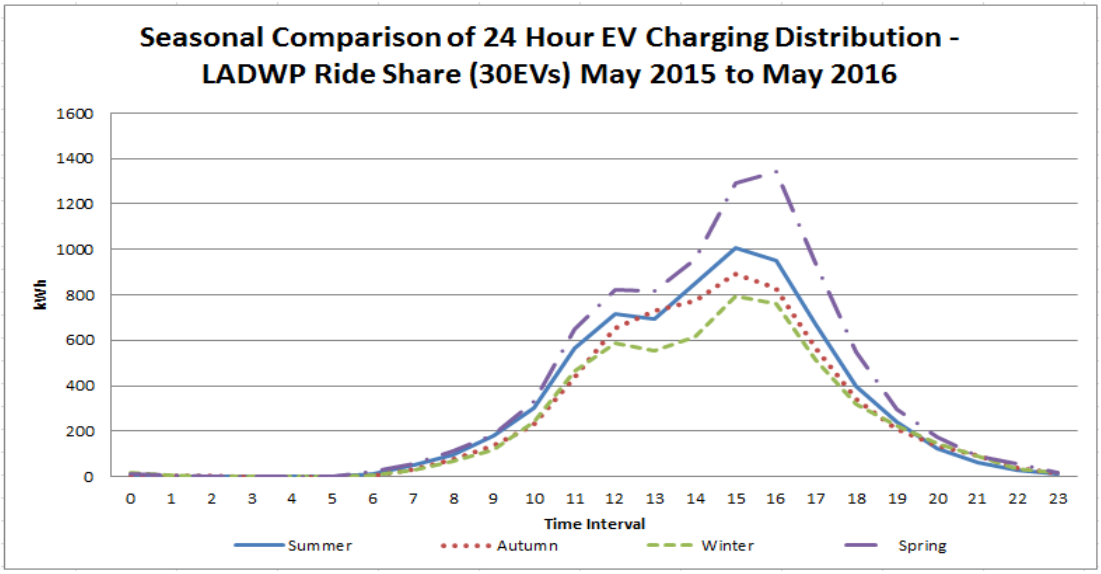


Figure 15 Seasonal Comparison of 24 Hour Cumulative Charging Energy Distribution of LADWP Ride Share (30 EVs) May 2015 to May 2016

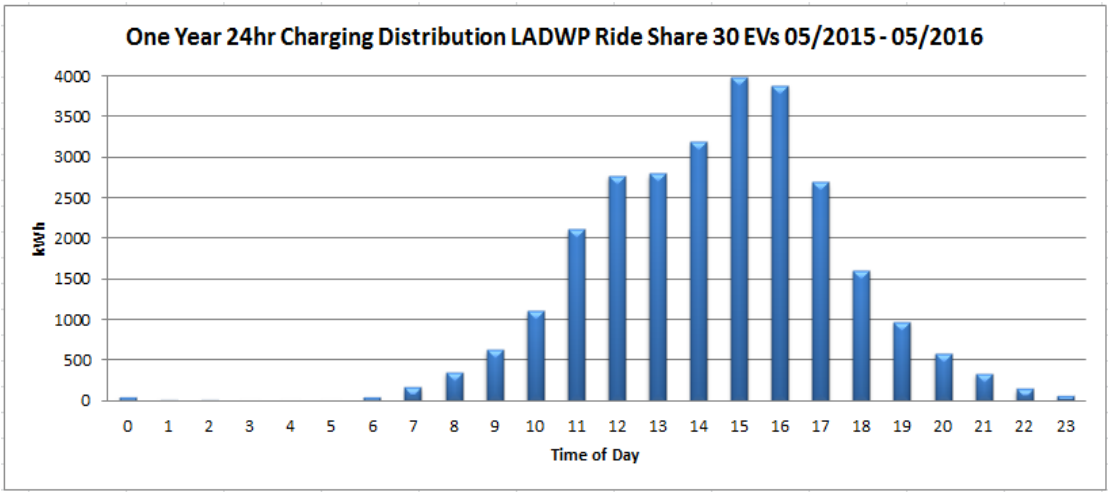


Figure 16 Cumulative 24 hour Energy Distribution of LADWP Ride Share (30 EVs) May 2015 to May 2016

List of Reports Published under this Demo

- Demo 18 Report –Report date June 10, 2016
- Statistical Analysis of Electric Vehicles Charging, Station Usage and Impact on the Grid – In proceedings of IEEE Innovative Smart Grid Technology (ISGT) 2016 (Pending)
- Analysis of Electric Vehicle Charging Impact on the Electric Power Grid – In proceedings of IEEE Transmission & Distribution-Latin America (T&D LA) 2016 (Pending)

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Disclaimers

The study results reported for Use Case 18 are based on the assumptions and data provided by LADWP and UCLA. No thorough review has been done to assess the accuracy of the data or the analysis models for the purpose of this study and thus, USC doesn't warranty the accuracy or the use of these study results.

Appendix X Technology Performance Report (TPR) Use Case (Demonstration) #19

Technology Performance Report (TPR)
Use Case (Demonstration) #19
July 15, 2016

Demo/Use Case Name: Car sharing programs: Distribution Effects of Car / Ride Share Program

Brief Description:

This demonstration studied EV users charging habits (type of EV, time of connection, duration, consumption, and if possible utilization). In this use case, customer profiles were analyzed and categorized. Based on this profiles economic analysis, models were created to study the impacts of large scale deployment of EV chargers in the applicable Use Cases.

Three types of EV users were analyzed. They are:

1. Large corporate LADWP users
2. Large corporate UCLA users
3. Typical owners of EVs in the residential areas within LADWP service territory

Design Document Methodology

Assumptions

The Car/Ride Share Center utilized the LADWP's car fleet that is designed to be used for day to day activities by personnel. The existing EV charging infrastructure was retrofitted to accommodate the new EV's charging standards. More than fifty EV cars from major manufacturers were purchased to be utilized in the fleet. The fleet was used to demonstrate the Distribution Effects of the EV Car/Ride Share program. In addition, EV charging start time, duration, energy and other charging information were collected from each charging station on daily basis for analysis purposes.

This program consisted of adding EVs to the existing fleet of LADWP cars. Along with the vehicles, additional parking spaces and signage was allocated in different LADWP locations depending on the determined need.

Demo responsibilities

The USC EV team obtained data from charger stations and study the customer's charging habits: charging times, duration, extent of charging and what effects these particular charging profiles would have on the distribution system. Once the customer profiles were analyzed and categorized, models were created to study the impacts of large scale deployment of EV chargers.

Additionally, according to the requirements of the Design Document, the USC team studied the charging patterns of EV usage by:

1) **Large corporate fleets** that have charging patterns similar to typical gas stations
2) Typical EV's that are employed **at a car rental**
3) **Typical owners** of EVs in the city and suburbs

Demo steps and flow

1. Collect data for more than 1 year to collect enough data to analyze and report results (except for the typical residential users data, where the available data was limited to three months)
2. Review EV charging data by time series (report each quarter)
3. Review EV usage data by time series (report each quarter)
4. Review any anomalies (Charging Stations or BMS errors) and report

Planned approach (as approved by DoE)

3. Monitor and Evaluate Data from Ride Share Program
4. Document and report on the Ride Share Program

Final Used Methodology

Key changes in Demo design and justification

Early in the study phase, it was recognized that "car rental" EV charging data will not be available for the study of Item 2: "Typical EV's that are employed at a car rental of the study plan." The availability of EVs within the car rentals was very limited and there was no known method of collecting this specific data. Thus, Item 2 was changed to: 2) Typical EV's that are employed at a university. Thus the three types of studies are:

1. Large corporate LADWP users
2. Large corporate UCLA users
3. Typical owners of EVs in the residential areas within LADWP service territory

The sources of data that were available for USC to study the customer's charging habit are listed below:

- One year survey data of LADWP employees driving EV, from June 2014 to July 2015
- EV usage data in FleetCarma, from May 2015 to May 2016
- LADWP dispatchers' data from May 2015 to May 2016
- Charging records of EVs that in University of Los Angeles, California from July 2014 to August 2015
- LADWP residential EV rebate meter data from Feb 2016 to April 2016

Data was collected not only from charging stations, but also from LADWP survey, FleetCarma, dispatch table, and electrical meters within LADWP service territory. To analyze the different types of usage habits, some of the Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicle (PHEV) were assigned to certain LADWP users. Usage information, charging

information, route information, and state of charge were recorded by FleetCarma. They were used to demonstrate the Distribution Effects of the EV Car/Ride Share program. This program consisted of adding EVs to the existing fleet of LADWP cars.

As a result, overview analysis and individual analysis could also be separated by assigned car, carpool car, BEV, and PHEV. Plus, user habit analysis needed a user name. However, charging and usage information should be obtained from FleetCarma. So LADWP provided dispatcher table which have users' name. According to dispatcher table, usage information could be selected by starting time and ending time.

This demonstration was divided into three tasks:

D. Car Usage, Charging Station Usage and Power Usage of large corporate fleet users:
   a) 36 assigned EV users
   b) 30 ride share users
E. Charging Station Usage and Power usage for each individual user in UCLA
F. Charging Meters Information and Power Usage of typical owners in LADWP local residential area from 2/1/2016 to4/30/2016.

Task A1: To meet the general system modeling and representation requirements of design document for a study on one year survey of EV users in LADWP, from June 2014 to July 2015, the following activities were performed by the USC EV research team:

5. Using habits and usage of EVs overview
6. Using habits of 20 EV heavy users
7. Comparison of using habits between users

Task A2: To meet the general system modeling and representation requirements of design document for charging habits, and car usage of 36 assigned EVs and 30 corporate EVs, the following activities were performed by the USC EV research team:

1. Overview of all EV usage and charging
2. LADWP assigned EV fleet, corporate EV fleet and charger overview
3. Individual EV's users habit analysis
   a. Charging patterns and using habits of 5 assigned BEV heavy users in LADWP from May 2015 to May 2016
   b. Charging patterns and using habits of 5 assigned PHEV heavy users in LADWP from May 2015 to May 2016
   c. Typical charging behavior obtained from FleetCarma
   d. Using habits of 5 corporate BEVs from May 2015 to May 2016.Usage distribution (number of trips start at each hour and average miles of trips start at each hour) from May 2015 to May 2016
   e. Usage distribution of top 5 heavy used carpool cars
4. Comparison of using habits between EV and non-EV. Comparison of using habits between corporate EVs and corporate ICEs.
5. Comparison of using habits between BEV and PHEV user habits, between assigned EVs and corporate EVs.

Task B: To meet the general system modeling and representation requirements of design document for the UCLA charging station usage and power usage, the following activities were performed by the USC EV research team:

4. Charging behaviors of 10 EV users in UCLA from 7/2014 to 8/2015

a. Energy transferred per day
b. Distribution of plug in start time
c. Histogram of Plug-in Time

5. Comparison of charging habits between users

Task C: To meet the general system modeling and representation requirements of design document for the charging usage and power usage of 10 typical residential EV users, the following activities were performed by the USC EV research team:

5. Distribution of electrical meters
6. Charging meter information and power usage of 10 typical residential EV users from 2/1/ 2015 to 4/30/2016
    a. Hourly
    b. Weekday vs. weekend
    c. Charging duration distribution
    d. Charged energy distribution
    e. Amount of energy charged in each hour
7. Comparison of charging habits between users

Technologies Deployed

List of systems/equipment deployment

- AMI Meters
- More than 1000 EV Chargers
- FleetCarma
- More than 60 Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification"**

Progress vs. success criteria

Task A1: Car Usage, Charging Station Usage and Power Usage of 36 assigned EV users:

5. Raw data and overall analysis - **Completed**
6. Individual EV user's habit analysis from June 2014 to July 2015- **Completed**
7. Comparison of all EV Users from June 2014 to July 2015 – **Completed**

Task A2: Car Usage, Charging Station Usage and Power Usage of 30 ride share users:

5. Overview of all EV usage and charging - **Completed**
6. Overview of LADWP assigned EVs and carpool EVs - **Completed**
7. Individual EV user habit analysis - **Completed**
8. Comparison of EV and non-EV - **Completed**
9. Comparison of all EV users - **Completed**

Task B: Charging Station Usage and Power usage for each individual user in UCLA :

4. Individual EV user habit analysis from 07/2014 - 08/2015 - **Completed**
5. Comparison of EV users in UCLA - **Completed**

Task C: Charging Meters Information and Power Usage of typical owners in LADWP local residential area:

5. Individual typical owner analysis from 2/1/2016 – 4/30/2016 - **Completed**
6. Comparison of typical owners - **Completed**

Observations and Results

Observations and Results

4. LADWP EV User Habit

a) LADWP EV User Habit Analysis From June 2014 to July 2015

In this section, a study on one year survey of EV users in LADWP, from June 2014 to July 2015, was analyzed. Due to the reason that the FleetCarma was installed at June 2015, there were few car records. The USC EV team saw that most of the trips happen during 6am to 5pm and the EVs were seldom used after 5pm, which was surmised that the EVs were only used by LADWP users during working time. Therefore, unlike other users, the EVs were not used for after-work activities.

EV users were willing to use their car for commuting. For instance, from 6am to 9am, the average distance was 9.2 miles, which was a reasonable average distance between office and home, and EVs may be used to drive to work. From 3pm to 6pm, the average mileage is 8 miles, which was similar to the distance from 6am to 9am. It is probable that the EV users were heading back to home.

b) LADWP EV User Habit Analysis From May 2015 to May 2016

Due to the reason that many EVs have records on FleetCarma, the EV usage information analysis was focused on data recorded from May 20th 2015 until May 20th 2016.

The total number of assigned car was 36. 22 of them were PHEV, 14 of them were BEV. Comparing the assigned BEV users and assigned PHEV users, they had similar number of trips, but the total miles were different. Additionally, the average PHEV user consumed 7510KWh which was 2774KWh higher than the average BEV user. The reason may be that BEV users worry about their EV's battery capacity, and so, they did not use their vehicles for long distance trips and did not use them until the battery was fully charged. The USC EV team saw that the average mile of BEV users was 5.49 miles which was much shorter than PHEV users' 8.18 average miles. However, PHEV users used their vehicles for long distance trips and in many trips; they would fully drain the battery in their vehicles. So, PHEV users consumed more energy and had longer mileages.

As for the Carpool EV, The USC EV team saw that most of the trips happened during 7am to 3pm. The time range was narrower than the assigned EVs. This was because these cars belonged to LADWP and carpool car users returned these cars before leaving. 70% trips of Carpool EVs were within 5 miles. The USC EV team concluded that Carpool BEVs were usually used for short trips, which may be the result of work requirements. Furthermore, the figures showed there were no peaks in the long distance, which was quite different from the distribution of assigned EVs. This was because all the carpool cars were mainly used for work purpose. Almost 90% trips occurred during the day time.

Although there were many differences in carpool users and assigned car users, the USC EV team saw that almost all of the distribution charts of assigned car BEVs and carpool BEVs were similar to each other. All the carpool users and assigned car users had the same energy

consumption habits on BEVs. All the BEV car users were willing to keep their EVs above 50% SOC, which indicated that customers feel the range anxiety.

5. UCLA EV User Habit Analysis

229 EV users were recorded at UCLA. EV charging events were recorded from 07/2014 to 08/2015. Energy transferred for the top 10 heavy users were studied and the plug-in start time and duration per charging were examined. The statistic results of individual users were used to provide information and practical insights for utility companies to make city planning and future installations of the EV charging infrastructures.

The results from EV charging energy transfer showed that the energy used for charging per day was mostly under a certain amount. The energy distribution was different among EV types.

From the Distribution of Plug-in Start Time, the USC EV team saw that 5 out of 10 users preferred to plug in their EVs before work hours. 1 user occasionally charged overnight.

From the comparison of 10 users, the USC EV team concluded that the EV user who had a small capacity battery would charge for small amounts of energy every day, but the plug-in time could be long.

6. Typical EV Owner Habit Analysis

In this part, 223 residential users were involved. Dates were obtained from the users' meters. Those meters recorded consumed electricity every 15 minutes during 2/1/2016 to 4/30/2016. To ensure the accuracy of the charging data, unrealistic dates were filtered.

The total amount of charged energy of 10 users was higher than 1300KWh. Although there was no trips information, using the average value of 3.5 miles/KWh, the USC EV team concluded that all of users drove their EV at least 4000 miles in three months. High level of usage of EVs led to frequent and long charging durations. Six users charged their EVs more than 100 times in three months. On average, they charged EV more than 1 time per day. However, the average charged energy of those users was not more than 17.66KWh. Although 17.66KWh is not small, the capacity of the battery is higher than 60KWh, which is much bigger than 17.66KWh. Frequent charging habit may be caused by worry about low power or long time at home.

Lessons Learned

- FleetCarma; Initial attempts to internally develop data monitoring and collection tools were not successful and. Having a commercially available collection system like FleetCarma was very helpful. However, FleetCarma had its own problems.
- There were difficulties to learn and use the data provided by FleetCarma due to the lack of certain information for direct analysis. Macros and algorithms were created in Microsoft Excel to replicate all data and plots on FleetCarma before processing the data. In the future, it would be desirable to have good documentation and vendor support to avoid the above mentioned issues.
- Data from UCLA; There were some discrepancy of the data format provided by UCLA. Data was only available from July 2014 to August 2015, no further data was provided after that.
- Data of EV charging in LADWP local residential area was only collected from February 1st to April 30th 2016.

Best Practices

None established.

Results of Data Collection

- Large amount of data was collected associated with this Use Case. This data was available in the USC data server for analysis. Some sample data analysis results for each of the Tasks were given in the following section.

Data Collection Summary (Graphs, Table, etc…)

1. LADWP EV User Habit

1.1 LADWP EV User Habit Analysis From June 2014 to July 2015

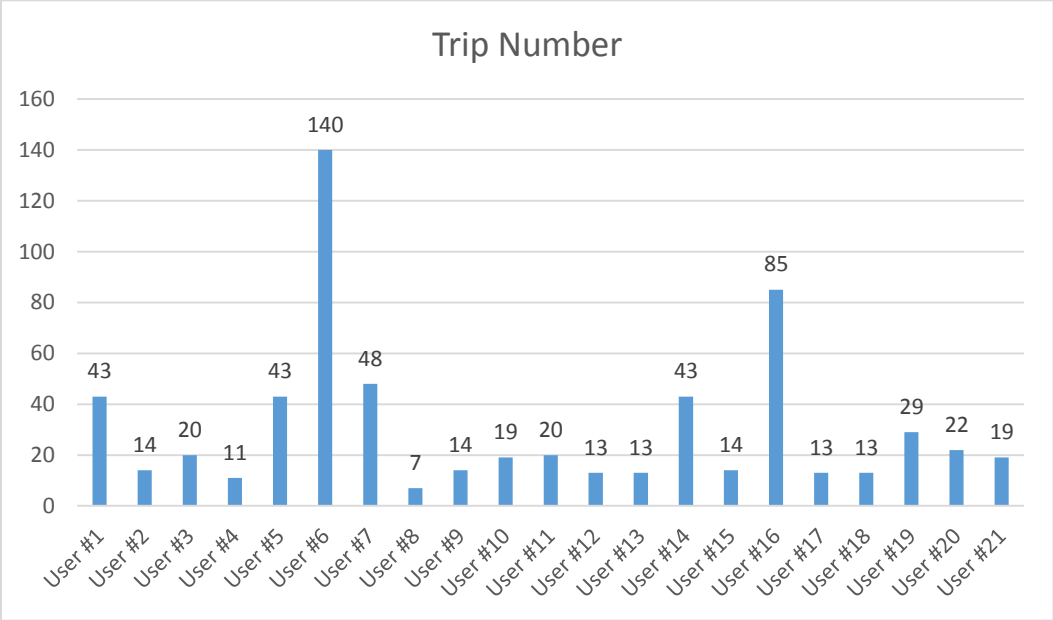


Figure 1 the Number of Trips for Each User

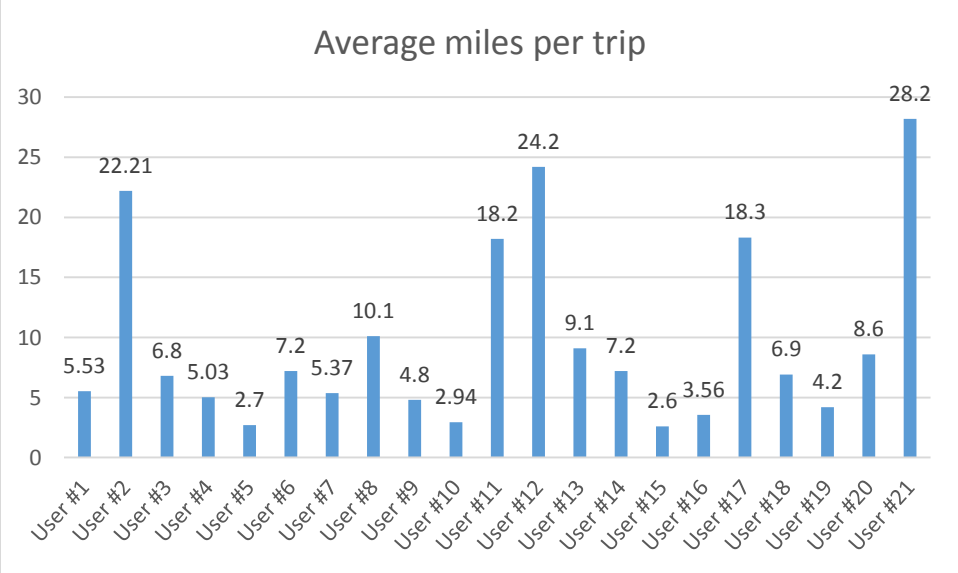


Figure 2 Average Miles per Trip for Each User

1.2 LADWP EV User Habit Analysis From May 2015 to May 2016

Table 1 Comparison of EV Users from May 2015 to May 2016

BEV	User Number	Number of Trips	Total Miles	Average Miles	Total Charged Energy(KWh)
	User 1	920	1502	1.63	673
	User 2	750	10168	13.56	2409
	User 3	663	2361	3.56	671
	User 4	434	2222	5.12	658
	User 5	264	400	1.52	325
Total		3031	16653	5.49	4736
PHEV	User 1	975	3569	3.66	1475
	User 2	640	2733	4.27	946
	User 3	568	7547	13.29	2125
	User 4	562	7302	12.99	1884
	User 5	467	5111	10.94	1080
Total		3212	26262	8.18	7510

Table 2 The Comparison between Assigned BEV and Carpool BEV

Assigned BEV	No.1	No.2	No.3	No.4	No.5	Total
Number of Trips	920	750	663	434	264	3031
Total Mileage(Mile)	1502	10168	2361	2222	400	16653
Average Mileage(Mile)	1.63	13.56	3.56	5.12	1.52	5.07
Charged Energy(KWh)	673	2409	671	658	325	4736
Carpool BEV	No.1	No.2	No.3	No.4	No.5	Total
Number of Trips	1010	996	979	976	879	4840
Total Mileage(Mile)	7803	7215	7803	7353	7217	37391
Average Mileage(Mile)	7.73	7.24	7.97	7.53	8.21	7.73
Charged Energy(KWh)	1718	1676	1762	1680	1660	8496

2. UCLA EV User Habit Analysis

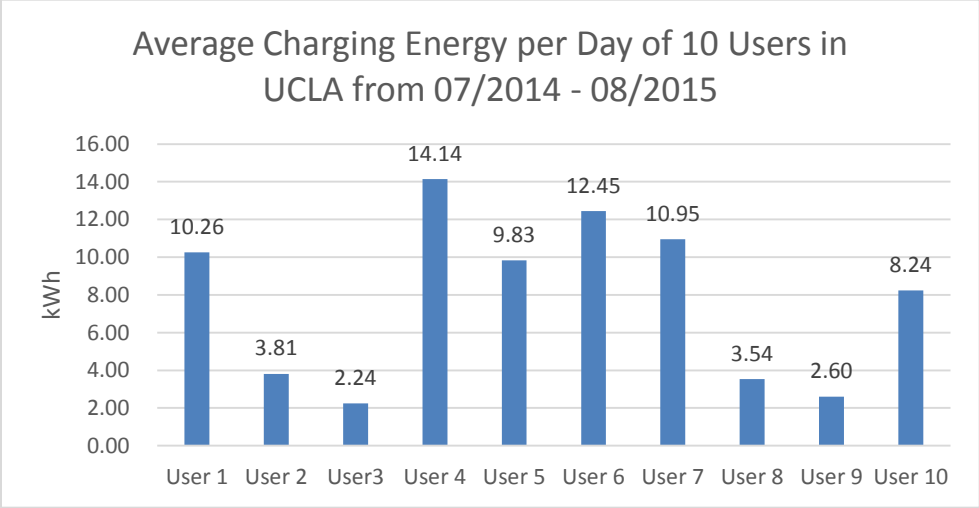


Figure 3 Average Charging Energy per Day of 10 Users in UCLA from 07/2014 - 08/2015

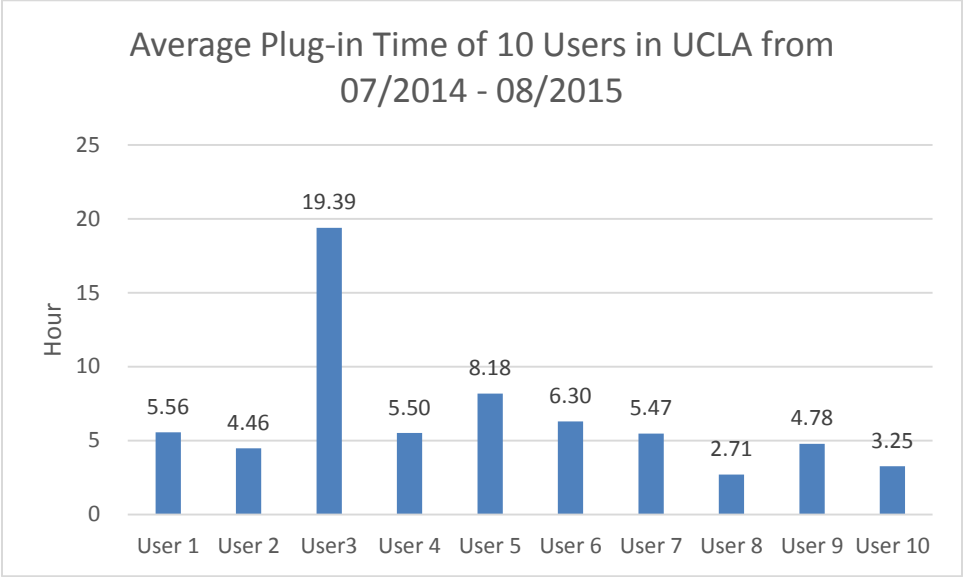


Figure 4 Average Plug-in Time of 10 Users in UCLA from 07/2014 - 08/2015

3. Typical EV Owner Habit Analysis

Table 3 Users Comparison

	User #2	User #3	User #4	User #5	User #6	User #7	User #8	User #9	User #10	User #11
Number of Charging	122	141	159	216	46	166	119	70	58	68
Charging Time(Hour)	275	268.75	447.25	538.25	235.5	452.5	306	167.75	114.75	151.25
Charged Energy(KWh)	2154.4	2081.3	1887.7	1746.8	1588.6	1493.1	1428.8	1386.6	1411.5	1368.6
Average Charging Time(Hour)	2.25	1.91	2.81	2.49	5.12	2.73	2.57	2.40	1.98	2.22
Average Charged Energy(KWh)	17.66	14.76	11.87	8.09	34.53	8.99	12.01	19.81	24.34	20.13

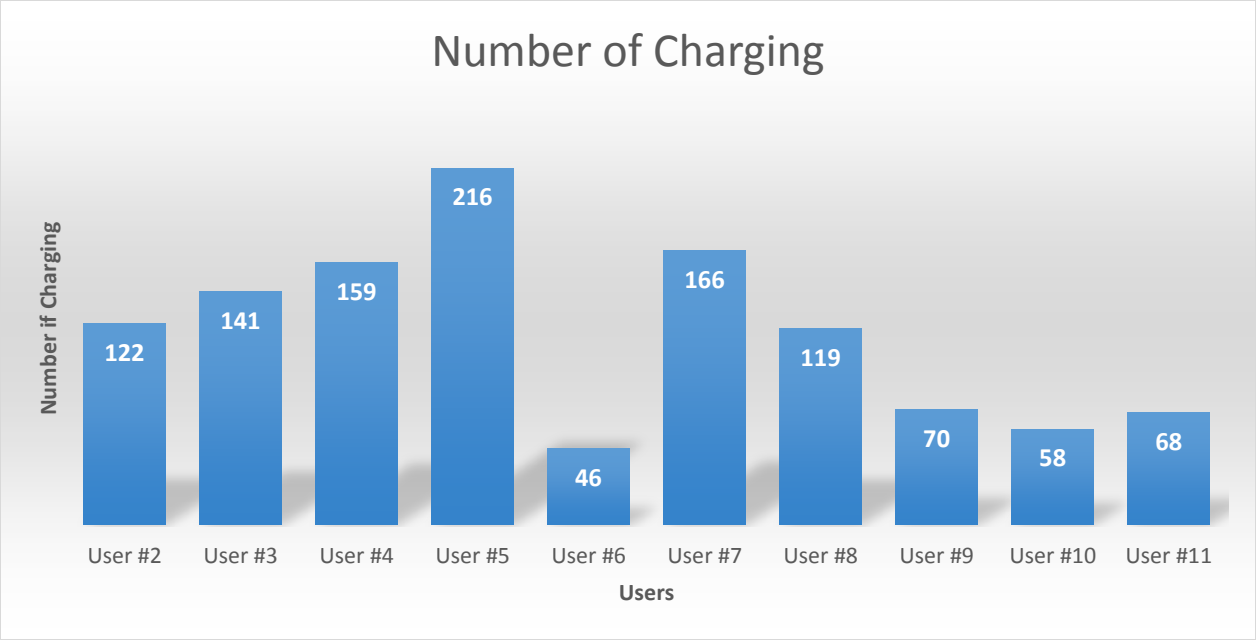


Figure 5 Number of Charging

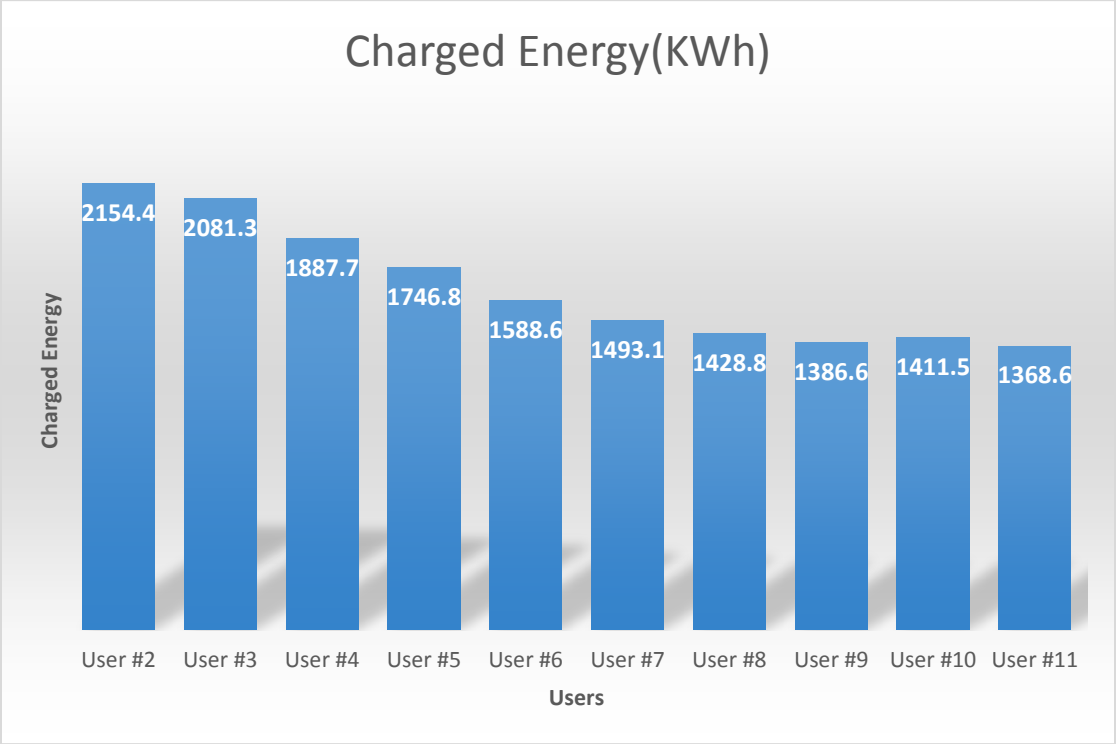


Figure 6 Charged Energy (KWh)

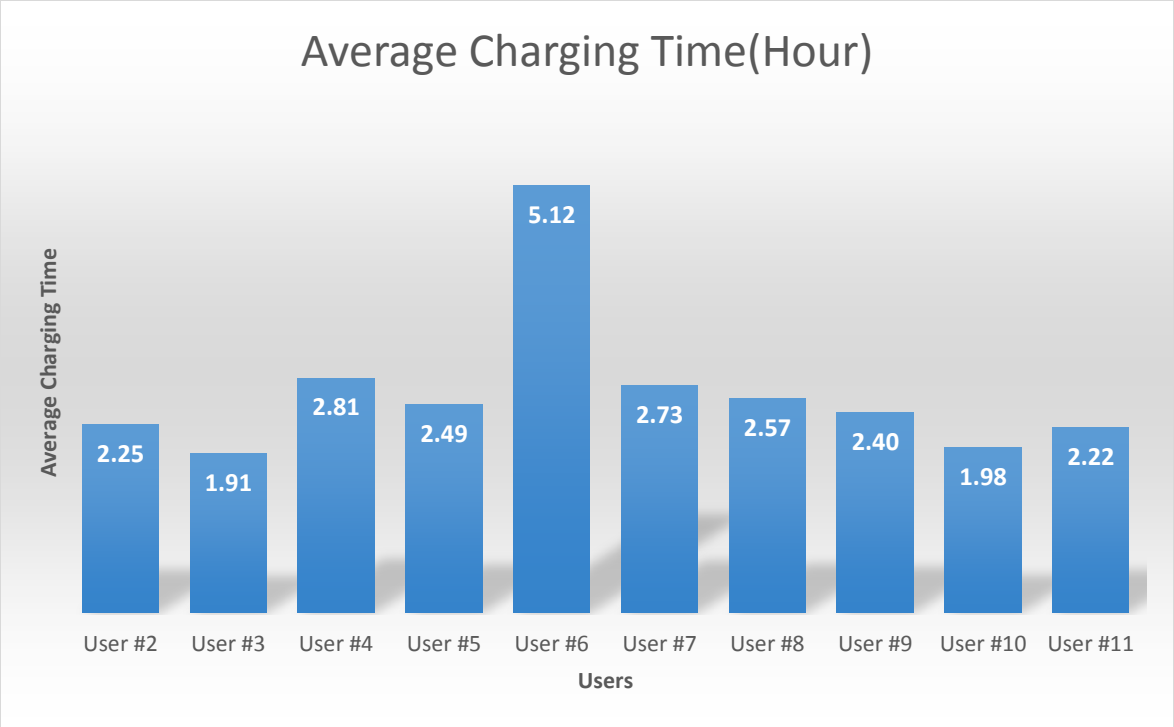


Figure 7 Average Charging Time (Hour)

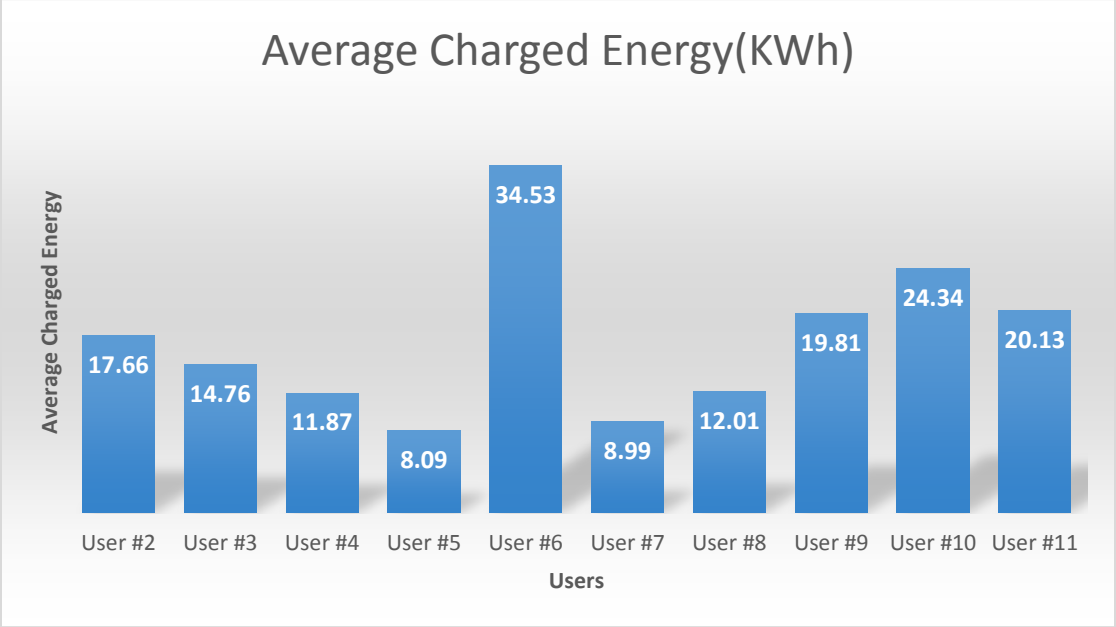


Figure 8 Average Charged Energy (KWh)

List of Reports Published under this Demo

Demo 19 Report –Report date July 15, 2016

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Disclaimers

The study results reported for Use Case 19 are based on the assumptions and data provided by LADWP and UCLA. No thorough review has been done to assess the accuracy of the data or the analysis models for the purpose of this study and thus, USC doesn't warranty the accuracy or the use of these study results.

Appendix Y Technology Performance Report (TPR) Use Cases (Demonstration) #21

Technology Performance Report (TPR)
Use Cases (Demonstration) #21
July 15, 2016

Demo/Use Case Name: Grid Impact: Various Loading Scenarios

Brief Description:

This Use Case evaluated EV loading on the distribution grid. Eight different loading scenarios were modeled and analyzed. The grid impacts to be studied under the requirements of Use Case or Demonstration #21 are listed as follows:

- Interaction of EV(s)
- Application of Battery storage
- Charging and discharging processes

Design Document Methodology

Assumptions

There were two demonstrations that were part of the Grid Impact category. These demonstrations included "Generation, Transmission, and Distribution Effects" of EVs (Use case #20); and EV effects of "Various Loading Scenarios" of the distribution system (Use Case # 21). USC was the primary researcher in this area, modeling systems to assess impacts, based on gathered data. To best perform these studies, USC created computer models to analyze the existing LADWP infrastructure and took information from various substations, distribution automation equipment, and various AMI meters throughout the LADWP service territory.

The specific assumptions for each case scenario are found in the demonstration report #19.

Demo responsibilities

The USC team studied the impact of EV on the distribution grid according to eight loading scenarios as indicated below in the Table below:

Loading Scenarios	Associated Research Question
1. Multiple EV charger Level 2 installations in the areas that have underground cables running in conduits.	To check whether the existing infrastructure can accommodate the additional current loading with Level 2 chargers
2. Multiple EV charger Level 2 installations that are serviced by industrial stations.	To check whether the existing infrastructure can accommodate the additional current loading with Level 2 chargers
3. Multiple EV charger Level 2 installations connected to pad-mount transformers.	To check whether the existing infrastructure can accommodate the additional current loading with Level 2 chargers
4. Multiple EV charger Level 2 installations in areas with feeders originating from Distributing Station which does not have voltage regulators. The feeder voltage is regulated using an auto tap changing transformer.	To check whether the existing infrastructure can accommodate the additional current loading with Level 2 chargers
5. Multiple EV charger level 3 installations connected to pad-mount transformers.	To check whether the existing infrastructure can accommodate the additional current loading with Level 3 chargers
6. Multiple EV charger Level 2 installation coupled with residential solar panel rooftop installation located in areas with different electricity pricing rates.	To study the potential mitigation of infrastructure requirements and economic benefit when renewable energy sources are locally integrated with EVs.
7. Multiple EV charger Level 2 installation coupled with battery storage located in areas with different electricity pricing rates.	To study the potential mitigation of infrastructure requirements and economic benefit when battery aggregation and backfill processes are locally integrated with EVs.
8. Multiple EV charger Level 2 installation coupled with residential solar panel rooftop installation and battery storage located in areas with different electricity pricing rates.	To study the potential mitigation of infrastructure requirements and economic benefit when renewable energy sources and battery aggregation and backfill processes are locally integrated with EVs.

Demo steps and flow

1. Run Use Cases (#2, #7, and # 17) for more than 1 year to collect enough data to analyze and report results.
2. Collect information and build circuit models to reflect different circuit scenarios like:
    a. Underground vs. Overhead
    b. Industrial vs. Residential

c. Pad-Mounted vs. Overhead Transformers
d. Voltage Control (regulators / capacitors)
e. Renewables (solar / battery)

3. Review Charging Station usage data by time series and create load models. Organize usage data by Charging Station Level (2 & 3).
4. Analyze above circuit configurations with different loading models created in step above.
5. Report finding in report.

Planned approach

Task A: System modeling and simulation studies will be conducted to create the system representation and test the use case.

Task B: System demonstration will be conducted using actual system data.

Final Used Methodology

Key changes in Demo design and justification

Task A: To meet the general system modeling and representation requirements of the design document, several issues needed to be considered: (1) type of system performance to be analyzed, (2) type and level of system modeling required, and (3) the size of system representation to be used. To assess the EV application effects of the various distribution system load scenarios, such as underground cables, regulating transformers, etc., the most critical considerations were system transients and harmonic issues. Thus, electromagnetic transient analysis methods were utilized to assess these system phenomena. For such analysis, only a very small system network model could be used (deviation from the use of the "existing LADWP infrastructure"). It was also necessary to assess the power flow implications of these various loading scenarios, thus a three-phase distribution mode was also used with the same system representation as the electromagnetic transient network model.

Taking the above discussed considerations, the following activities were under taken by the USC EV research team:

1. One set of distribution network models was selected to enable analysis of EV distribution effects as described in the SGRDP Preliminary Design Document. The network model selected was the IEEE 34 bus test system reflecting an industry standard distribution test model.
2. Two software programs were selected for the development of these models. These software programs were:
    a. Distribution system modeling software Distribution Engineering Workstation (DEW) by Electrical Distribution Design, Inc. (EDD) is to be used to model the distribution network
    b. Power system modeling software Power system Computer Aided Design (PSCAD) by Manitoba HVDC Research Centre is to be used to model the generation, transmission and distribution networks, as well as testing and analyzing the harmonic issues
3. The EDD and PSCAD models and the IEEE 34 system representations allowed the attachment of multiple EV-charger loads of various classifications
4. The EDD and PSCAD models and the IEEE 34 system representations were designed to reveal the aggregate effect of the multiple EV-charger loads at substation connections to the transmission grid.

5. The various loading scenarios were tested using EDD and PSCAD models.
6. Using PSCAD harmonic analyses were setup on the test systems with the goal of revealing when the IEEE 34 system will encounter the most severe harmonics when multiple EV loads as well as renewable energy are connected.

Task B: System demonstration using actual system data was not performed due to the lack of available metered data. The sources of this issue included: (1) lack of tools and capability to represent the vast LADWP infrastructure at Chatsworth in electromagnetic transient analysis model, (2) lack of the metering infrastructure to cover a sufficient amount of the LADWP system, and (3) extensive delay in the implementation of the data collection of system

Technologies Deployed

List of systems/equipment deployment
The following items were planned for deployment in the Chatsworth area to support this and other use-cases. However none of these were fully deployed and used as discussed above.

- AMI Meters (Residential, C&I, EV)
- Up to 10 EV Chargers
- DA/SA Equipment
- MDM
- Electric Vehicles

Table summarizing planned construction vs. actual
None of the installations identified above were used for these demonstration.

Success Criteria

Description of success criteria for this Demo
To conduct the work activities outlined under the "**Key changes in Demo design and justification"**

Progress vs. success criteria
Task A: To meet the general system modeling and representation requirements of the design document, the following activities were performed by the USC EV research team:

1. Select a network model to enable analysis of EV distribution effects as described in the SGRDP Preliminary Design Document. **- Completed**
2. Select software programs for the development of the model. **- Completed**
3. Attach multiple EV charger loads of various classifications to the EDD and PSCAD models and the IEEE 34 system. **- Completed**
4. Reveal the aggregate effect of multiple EV charger loads at substation connections to the transmission grid using the EDD and PSCAD models and the IEEE 34 system representations. **- Completed**
5. Test various loading scenarios using EDD and PSCAD models. **- Completed**
6. Using PSCAD harmonic analyses are setup on the test systems with the goal of revealing when the IEEE 34 system will encounter the most severe harmonics when multiple EV loads as well as renewable energy are connected. **- Completed**

Task B: Demonstrate system using actual system data. **Not Done**

Changes in success criteria

Equipment deployment in Task B was heavily reduced due to the reduction in the anticipated EV penetration in Chatsworth. This impacted in the scope of test case of Task B.

Observations and Results

Observations and Results

- Some high-level observations are outlined below based on the PSCAD simulation studies:
  - For the customers, charging the EV battery with higher SOC could cause less damage to both the grid and the battery.
  - For the EV charging station installation, the locations should be chosen far away from transformers, which are not only suffering the harmonic impact of EVs but are also acting as a harmonic source.
  - EV charging stations near industrial areas should have limits on the number of EVs and be equipped with protective systems to guarantee high power quality.
  - Underground cable is more susceptible to EV harmonics impacts than the overhead transmission line. This also requires higher requirements and standards for charging stations in this area.
  - EV charging station near the renewable resource, which itself is a harmonic sources, would need to include mitigation from the harmonic in the system. However, system mitigation, such as installing filters, should be considered to guarantee the power quality from the charging station.

  - Some high-level observations are outlined below based on the EDD simulation studies: Installing a voltage regulator at bus may increase the number of electric vehicles that can be integrated to the system, if the limiting conditions are voltage drop issues. Generally, regulating the voltage in a distribution system when electric vehicles are charged is not only related to the buses loaded, it is a matter of the entire system. The system must be tested to find the best location to install voltage regulators.
  - Overhead distribution lines are able to withstand more electric vehicles to be charged compared to underground cable.

Lessons Learned

- The design document requirement to construct LADWP infrastructure network for the system analysis for this Use Case was not realistic. It was beyond the scope of the demonstration work to develop electromagnetic transient analysis modeling of any significant size of the LADWP system.
- A reduced set of scenarios were done with EDD program, since harmonic analysis was not possible with this model
- Studies using a smaller system representation of the IEEE34 bus system were sufficient to assess the impact of the loading scenarios.
- Observations based on the simulation studies of the IEEE 34 bus test system are only possible. Equipment deployment, and about one-years of data collection will be needed to conduct the actual system demonstrations.

Best Practices

None established.

Results of Data Collection

- Various data collected using two separate studies to assess the harmonics generated as well system voltage profiles issues under the eight load scenarios.

Data Collection Summary (Graphs, Table, etc…)
None for the purposes of this use case.

List of Reports Published under this Demo

- Demo 21 Report – Progress Report date December 31, 2014
- IEEE publication – 2014 IEEE International Conference on Control Science and Systems Engineering (CCSSE 2014), Yantai, China, Dec 29-31, 2014
- The impact of distribution feeders that do not have voltage regulators on the number of charged electric vehicles using IEEE 34 bus test feeder, 4th International Conference on Clean and Green Energy (ICCGE 2015), Amsterdam, Netherlands, Feb. 14-15, 2015

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo
None established. Only simulations were planned.

Realized Impacts and Benefits to Date
None established. Only simulation results are available.

Disclaimers

The study results reported for Use Case 21 are based on the assumptions and data discussed in the report and are conducted using PSCAD and EDD analysis models. No through review has been done to assess the accuracy of the data or the analysis models for the purpose of this study and thus, USC doesn't warranty the accuracy or the use of these study results. The EDD and PSCAD power system analysis models are preparatory models supplied by the respective venders.

Appendix Z UCLA TPR Use Case 1

Technology Performance Report (TPR)
Use Case (Demonstration) #1
June 25, 2016

Demo/Use Case Name: Monitoring of All Chargers

Brief Description:

The purpose of this use case was to display the status of all chargers and indicate whether or not the charger was charging. To fulfill this task, a control and monitoring center was used to monitor all the charging behaviors at UCLA campus. In addition, a data collection service and a database system were developed to periodically retrieve the charging requests and store the status.

Design Document Methodology

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. The infrastructure consisted of a control center, mesh communication network, and the controllable Electric Vehicle Supply Equipment. The UCLA EV team's WINSmartEV platform was used to monitor and collect data from all of the EV chargers at the UCLA campus.

Demo responsibilities

This demonstration displayed the status of all EV chargers to indicate whether and when charging was occurring. This demonstration took place at the SG Power Lab, various Demo Sites, and the SG EV Control Center, and was executed primarily UCLA personnel. The demonstration provided detailed, on-demand charger information that indicated both the status of the charger and a regular transmittal of charging duration. The EV charger communicated directly with the SG EV Control Center through an application interface provided by the charger vendors, as well as additional metering devices, where feasible.

The EV project team installed charging stations from various vendors at UCLA & LADWP parking structures. These charging stations included Level 1, Level 2 and Level 3 charging.

However, as most charging stations used proprietary communication protocols, the EV Team was unable to obtain detailed user data and fully control the charging operations from the SG EV Control Center. Due to this limitation, the UCLA EV team designed and developed an open-architecture charging station that supported the data collection and circuit control of this project. These charging stations were implemented to provide the following functions:

1. Open architecture to collect user and vehicle profile, kW, usage history, etc.

2. Battery aggregation to provide dynamic charging scheme based on various inputs
3. Level 1 and Level 2 charging support
4. Safety and security factors in the design
5. Backfill integration

The UCLA EV team created an interface with commercial-off-the-shelf (COTS) chargers to collect charger data to allow the SG EV Control Center to monitor all chargers installed during this project. The SG EV Control Center provided a visualization portal to monitor the status of all chargers with a graphical interface to indicate the geographical location of the charger and its usage.

Demo steps and flow

1. Control Center sends station status request
2. Station receives status request command from Control Center
3. Station sends back to Control Center, status message
4. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data

Planned approach

5. Develop bi-directional communications between the Electric Vehicle Supply Equipment and the Control Center
6. Support different power information signal formats
7. Perform test procedures every 15 minutes or less
8. Monitor and evaluate data from all EV chargers

Final Used Methodology

Key changes in Demo design and justification

There were no key changes to the Demonstration design.

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- 137 EV Chargers (Level 1, 2, and 3)
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the **"Key changes in Demo design and justification"**

Progress vs. success criteria

1. Control Center sends station status request – **Complete**
2. Station receives status request command from Control Center – **Complete**
3. Station sends back to Control Center, status message – **Complete**
4. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data – **Complete**

Observations and Results

Observations and Results

Based on the above analysis of the system design and the implementation, it was demonstrated that this system was able to effectively monitoring charging behaviors, in terms of voltage, current, power consumption, total energy consumption, as well as the detailed start time, end time and the stay duration for each charging session. All of these data were reported to the control center successfully. The detailed data collected helped study charging behaviors. The DCFC had the best charging efficiency and could serve the emergent charging events rapidly while the level l charging infrastructures were more suitable for the user who had regular charging routine and could stay longer. Those detailed data were so valuable that they could be used for charging behavior estimation and thus could achieve charging optimization. More accurate estimation could be made when collecting more data. For example, a specific user's charging routine, such as charging start time, end time, charging mode, battery SOC, or energy consumption, would help the control center to optimize the overall charging events. In addition, the general monitoring page for all charging behaviors and the detailed monitoring chart for each EVSE were developed for further analysis.

Lessons Learned

None established.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected numerous data points from 136 Level 1 and Level 2 EV chargers for 5 months. These data points include the name, timestamp, voltage, current, frequency, power factor, active power, apparent power, and main energy.

- Additionally, the UCLA EV team collected data points from 1 Level 3 EV charger for 5 months. These data points include the time, voltage, current, total main energy, and total active power.

Data Collection Summary

UCLA EV Activbe Charging Station Status				As of 02/29/2016
Location	Voltage	Connector type	Plug Points	Network/Status
LADWP JFB Lot 6 Level 2	110 V	NEMA 5-15	4	3G
PS 9 Level 4	110 V	NEMA 5-15	4	V2G testing
PS 9 Level 6	110 V	NEMA 5-15	4	WiFi,
PS 8 level 2 North	110 V	NEMA 5-15	4	3G
PS 8 level 2 South	208 V	J1772	4	3G
PS 8 level 2 North	208 V	J1772	4	3G
PS 2 level 2	110 V	NEMA 5-15	4	3G
PS 3 level 4	110 V	NEMA 5-15	4	3G
PS 3 level 2	208V	J1772	4	3G
PS 4	208 V	J1772	8	wired
PS 2	208 V	J1772	4	3G
UCLA Medical Center	208 V	J1772	4	wired
Sunset Village Parking (fleet)	110 V	NEMA 5-15	84	wired and Wif
Nissan Level 3 Charger (PS 4)	480 VAC	CHAdeMO	1	wired and Wif

Table 1: Participating Charging Stations





Figure 1: Sunset Village Installation



Figure 2: Level 2 EVSE with Emergency Cutoff Switch on the Right Side

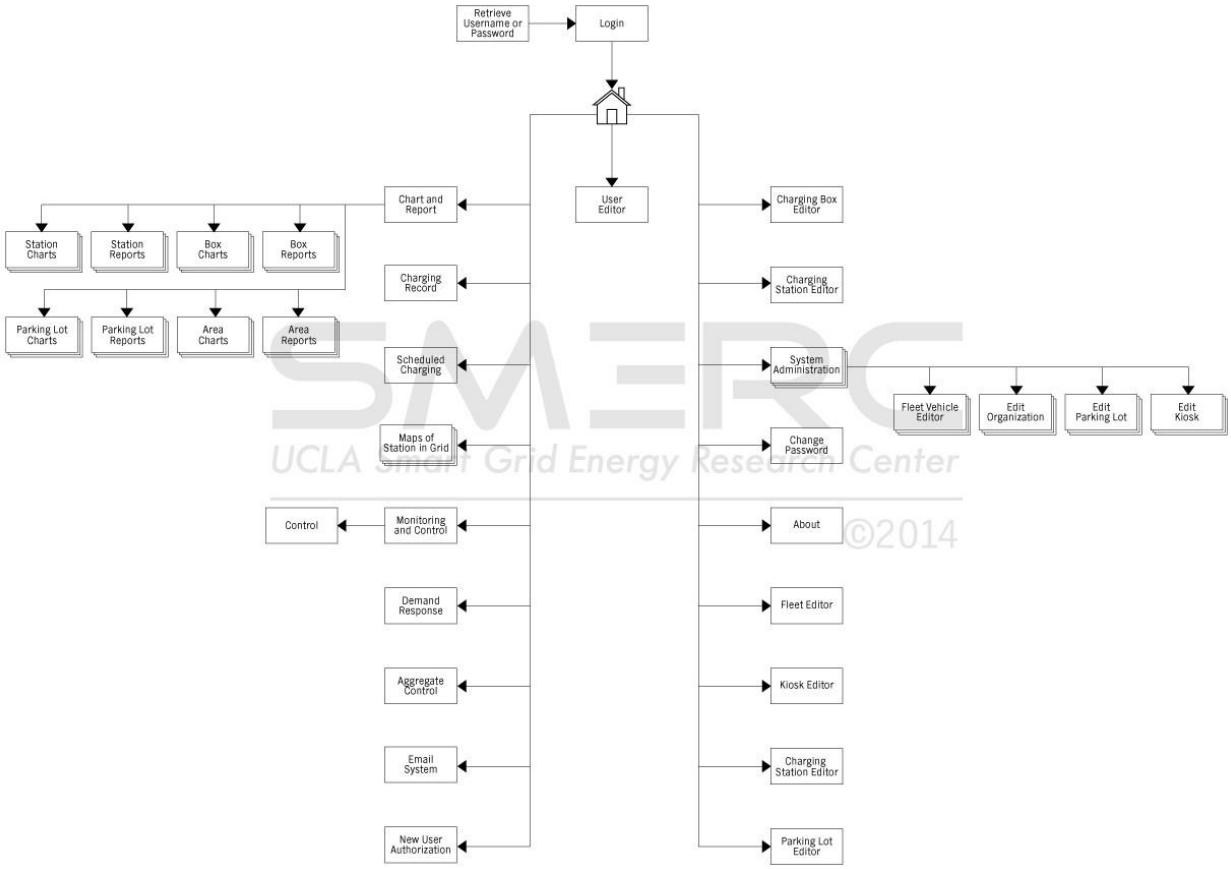


Figure 3: Monitoring and Control Center Site Map



PS3L201LII — Energy Sharing L2 S — 2 — 3G/4G

- Charging Stations

Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information
PS3L201LII01	Standby	On	No	0%	1	-	
PS3L201LII03	Charging	On	Yes	25%	3		Nissan Leaf 24kWh
PS3L201LII04	Charging	On	Yes	25%	4		Ford Fusion Energi 7.6kWh

PS3L401LI — Energy Sharging L1 M — 1 — 3G/4G

- Charging Stations

Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	Time
PS3L401LIA1	Standby	Off		-	A1	-		03/31/201
PS3L401LIA2	Standby	Offline		-	A2	-		03/31/201
PS3L401LIA3	Standby	Offline		-	A3	-		03/31/201
PS3L401LIA4	Standby	Offline		-	A4	-		03/31/201

PS4, 221 Westwood Plaza, Los Angeles, CA90095

PS4P101LII — Energy Sharing L2 S — 2 — Ethernet

- Charging Stations

Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	
PS4P101LII01	Charging	On	Yes	25%	1		Chevrolet Volt 16kWh	03/3
PS4P101LII02	Standby	On	No	0%	2			03/3
PS4P101LII03	Standby	On	No	0%	3			03/3
PS4P101LII04	Charging	On	Yes	25%	4		Nissan Leaf 24kWh	03/3

PS4P102LII — Energy Sharging L1 M — 1 — Ethernet+WiFi

- Charging Stations

Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	Time
PS4P102LII01	Standby	Off		-	1	-		03/31/201
PS4P102LII02	Standby	Off		-	2	-		03/31/201
PS4P102LII03	Standby	Off		-	3	-		03/31/201
PS4P102LII04	Standby	Off		-	4	-		03/31/201

PS8, 555 Westwood Plaza, Los Angeles, CA90095

PS8L201LI — Energy Sharging L1 M — 1 — 3G/4G+WiFi

- Charging Stations

Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	Time
PS8L201LIA1	Standby	Off		-	1	-		03/31/201
PS8L201LIA2	Standby	Off		-	2	-		03/31/201
PS8L201LIA3	Standby	Off		-	3	-		03/31/201
PS8L201LIA4	Standby	Off		-	4	-		03/31/201

PS8L202LII — Energy Sharing L2 S — 2 — 3G/4G

- Charging Stations

Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information
PS8L202LIIA0	Charging	On	Yes	12%	1		Chevrolet Volt 16kWh
PS8L202LIIA1	Charging	On	Yes	12%	2		Toyota Prius Plug-in 4kWh
PS8L202LIIA2	Charging	On	Yes	50%	3		Volkswagen E-Golf 24kWh

PS8L203LII — Energy Sharing L2 S — 2 — 3G/4G

- Charging Stations

Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information
PS8L203LIIA1	Charging	On	Yes	12%	1		Chevrolet Volt 16kWh
PS8L203LIIA2	Charging	On	Yes	12%	2		Chevrolet Volt 16kWh
PS8L203LIIA3	Charging	On	Yes	12%	3		Ford C-Max Energi 7.6kWh
PS8L203LIIA4	Charging	On	Yes	12%	4		Chevrolet Volt 16kWh

PS9, 675 Charles E. Young Dr, Los Angeles, CA90095

PS9L601LI — Energy Sharging L1 M — 1 — WiFi

- Charging Stations

Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	
PS9L601LIA2	Standby	Offline		-	2		Chevrolet Volt 16kWh	03/3
PS9L601LIA4	Standby	Offline		-	4			03/3

Figure 4: Monitoring Page on EV Control Center



Charging Info between 03/19/2016 00:00:00 and 03/19/2016 23:59:59

Power Slot	User Name	Manufacturer	Model	Start Time	End Time	End	Ended By User	Charging Times	Energy Price	Energy Consumed	Charging Cost
3		Chevrolet	Volt 16kWh	3/19/2016 8:09:54 PM	3/20/2016 12:16:40 AM	✓		1	20.00	12.1100kWh	$2.42
4		Chevrolet	Volt 16kWh	3/19/2016 12:15:04 PM	3/19/2016 1:21:39 PM	✓		1	20.00	3.2570kWh	$0.65

PS8L203LII

PS8L203LII 1
PS8L203LII 2
PS8L203LII 3
PS8L203LII 4

03/19 08:00:00
03/19 12:00:00
03/19 16:00:00
03/19 20:00:00

Figure 5: Charts for Charging Behaviors at Specific EVSE

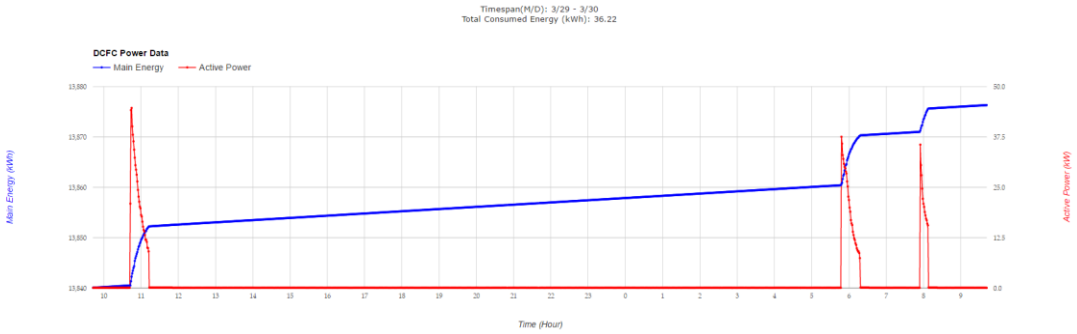


Figure 6: DCFC Power Consumption Monitoring

	A	B	C	D	E	F	G	H	I	J
1	**Name**	**Timestamp**	**Voltage**	**Current**	**Frequency**	**Power Factory**	**Active Power**	**Apparent Power**	**Main Energy**	**ChargingStatus**
2	PSVP4HLIH8	10/1/15 9:39 PM	0	0	0	0	0	0	0	Idling
3	PSVP4HLIH8	10/3/15 12:19 AM	0	0	0	0	0	0	0	Idling
4	PSVP4HLIH8	10/4/15 3:02 AM	0	0	0	0	0	0	0	Idling
5	PSVP4HLIH8	10/5/15 5:44 AM	0	0	0	0	0	0	0	Idling
6	PSVP4HLIH8	10/6/15 8:27 AM	0	0	0	0	0	0	0	Idling
7	PSVP4HLIH8	10/7/15 11:09 AM	0	0	0	0	0	0	0	Idling
8	PSVP4HLIH8	10/8/15 1:50 PM	0	0	0	0	0	0	0	Idling
9	PSVP4HLIH8	10/9/15 4:34 PM	0	0	0	0	0	0	0	Idling
10	PSVP4HLIH8	10/10/15 7:19 PM	0	0	0	0	0	0	0	Idling
11	PSVP4HLIH8	10/11/15 9:43 PM	0	0	0	0	0	0	0	Idling
12	PSVP4HLIH8	10/12/15 11:59 PM	0	0	0	0	0	0	0	Idling
13	PSVP4HLIH8	10/14/15 12:18 AM	117.32	0	60.1	1	0	0	240.865	Idling

Figure 7: Sample Data File for Level 1 and Level 2 Chargers

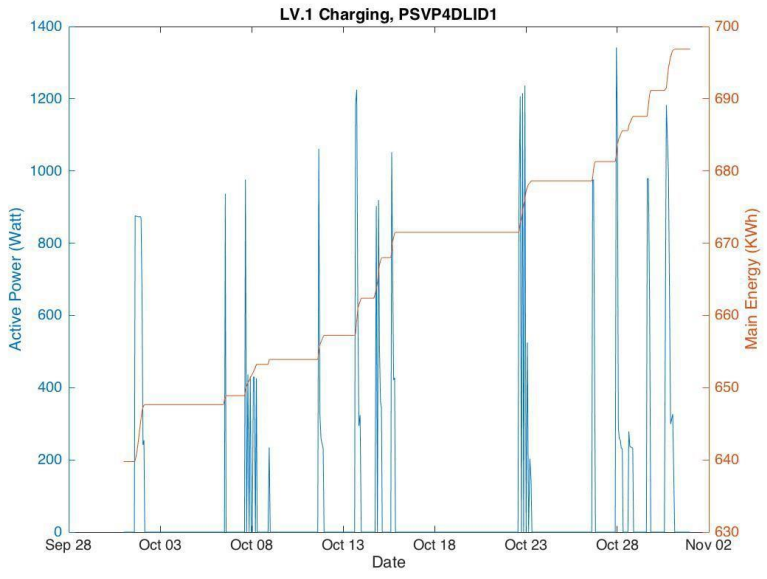


Figure 8: Power Consumption and Main Energy for Level 1 Charging for October 2015

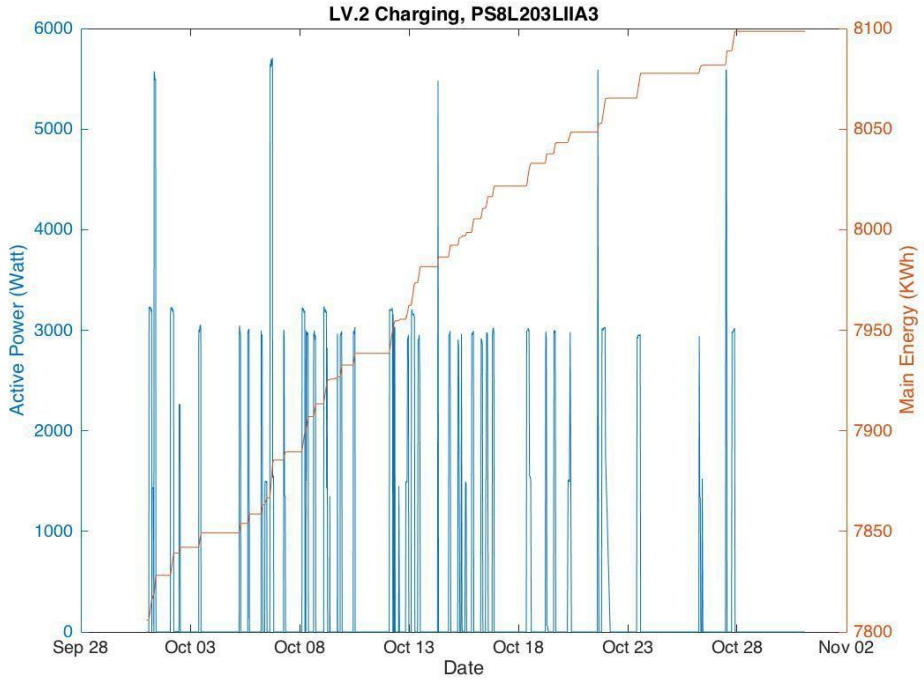


Figure 9: Power Consumption and Main Energy for Level 2 Charging for October 2015

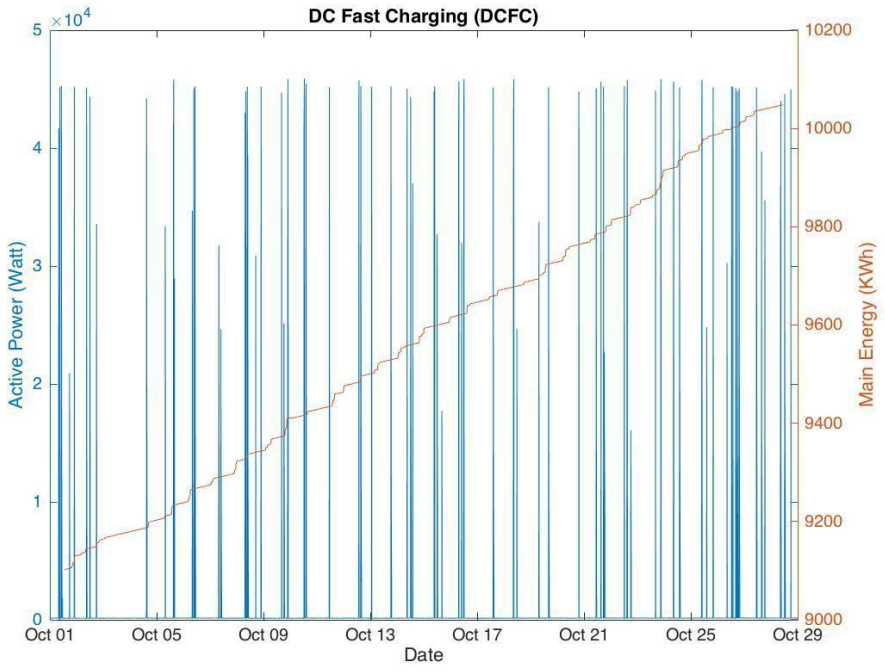


Figure 10: Power Consumption and Main Energy for DC Fast Charging for October 2015

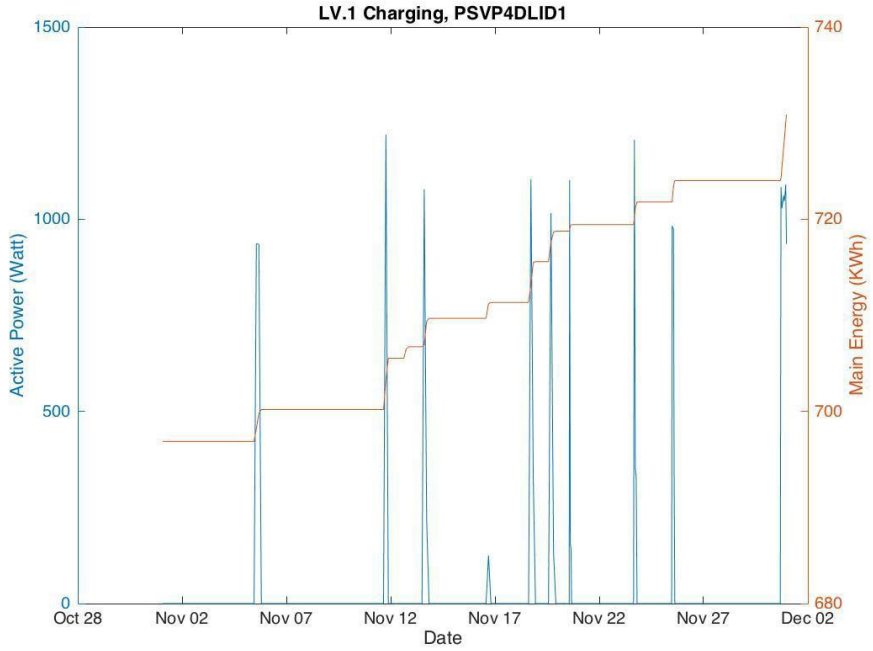


Figure 11: Power Consumption and Main Energy for Level 1 Charging for November 2015

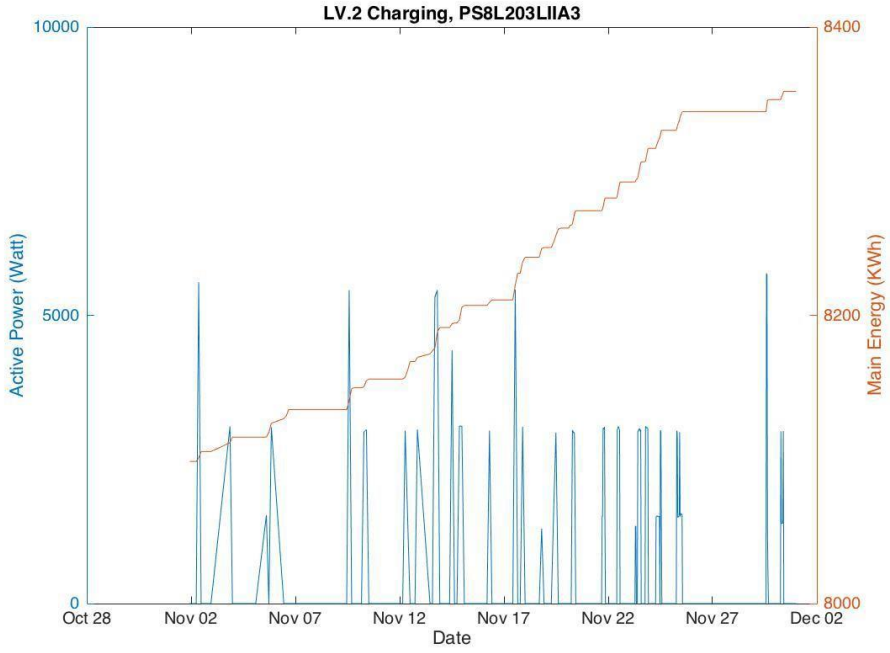


Figure 12: Power Consumption and Main Energy for Level 2 Charging for November 2015

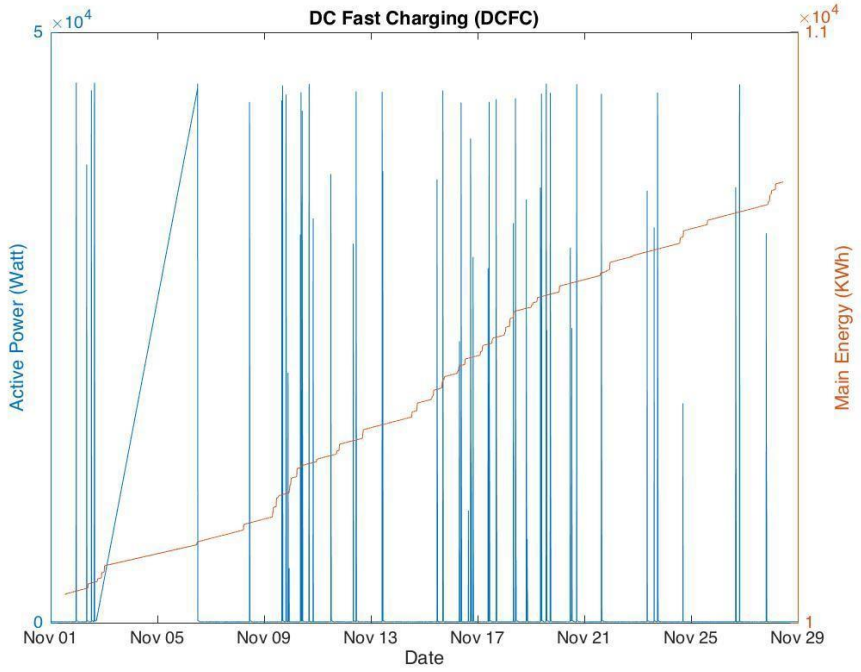


Figure 13: Power Consumption and Main Energy for DC Fast Charging for November 2015

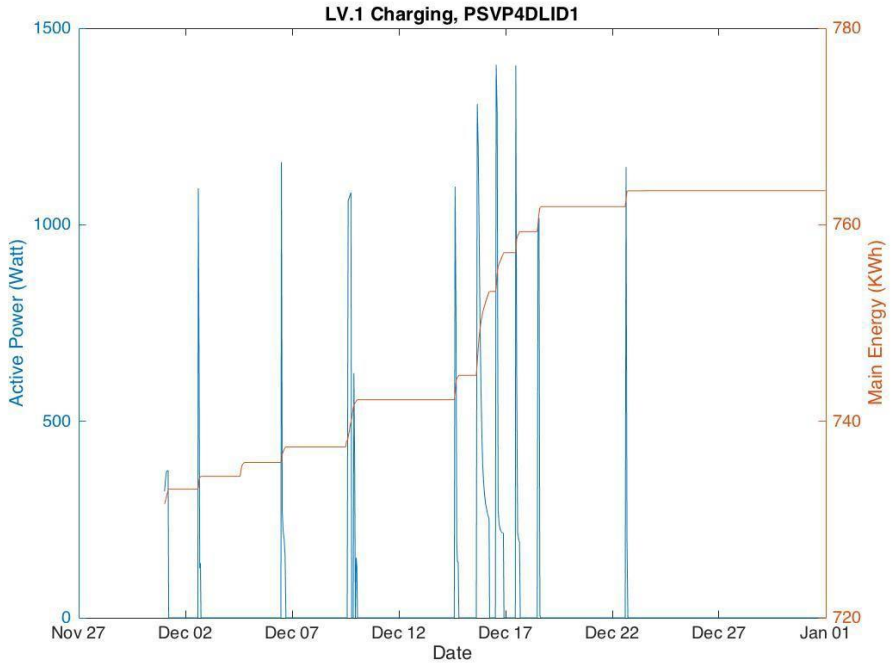


Figure 14: Power Consumption and Main Energy for Level 1 Charging for December 2015

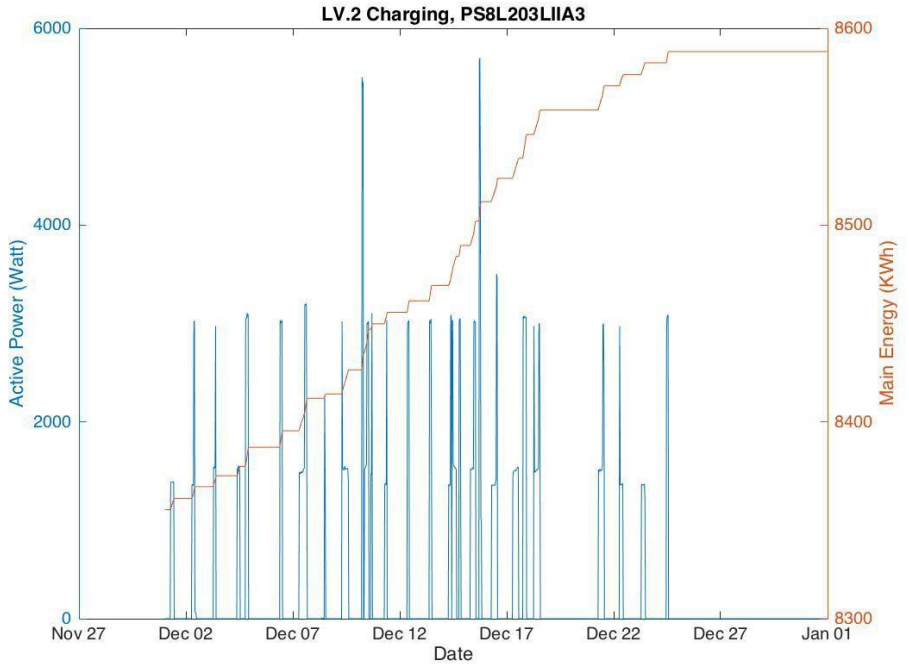


Figure 15: Power Consumption and Main Energy for Level 2 Charging for December 2015

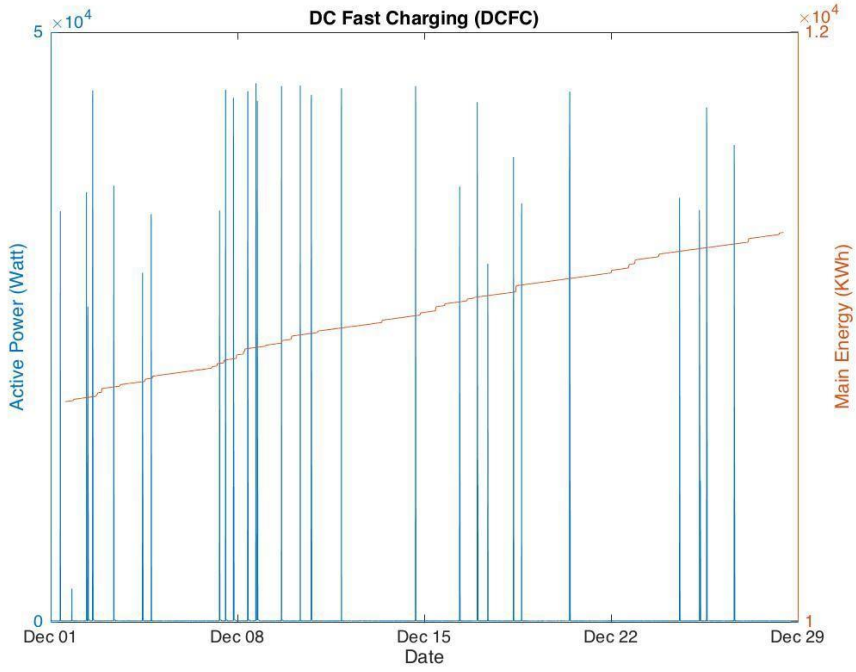


Figure 16: Power Consumption and Main Energy for DC Fast Charging for December 2015

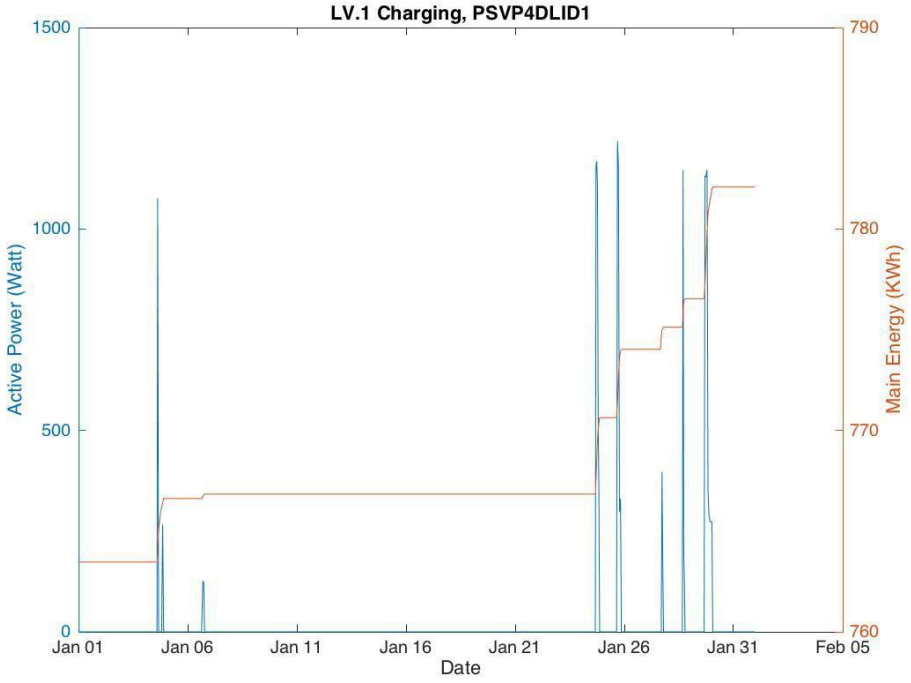


Figure 17: Power Consumption and Main Energy for Level 1 Charging for January 2016

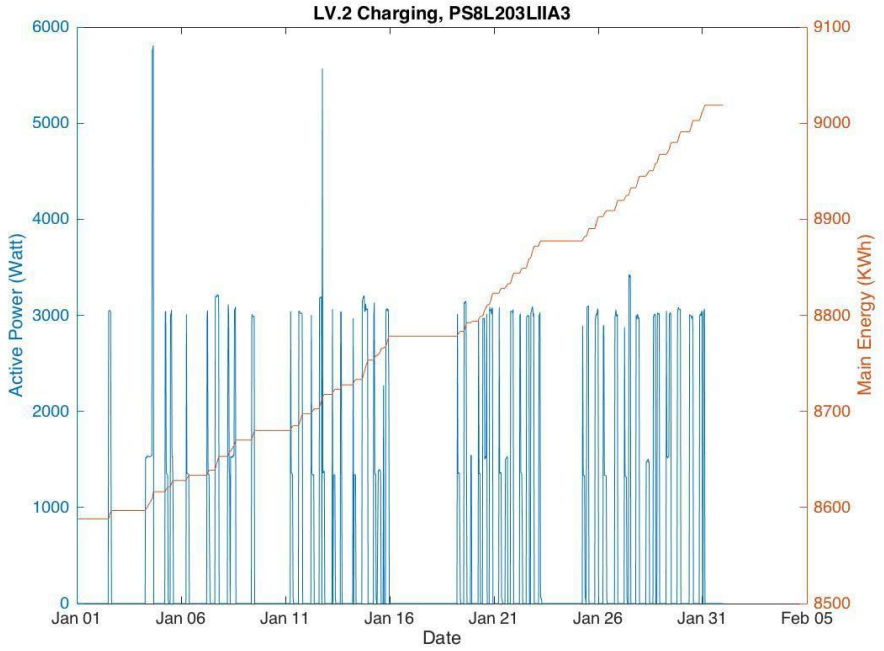


Figure 18: Power Consumption and Main Energy for Level 2 Charging for January 2016

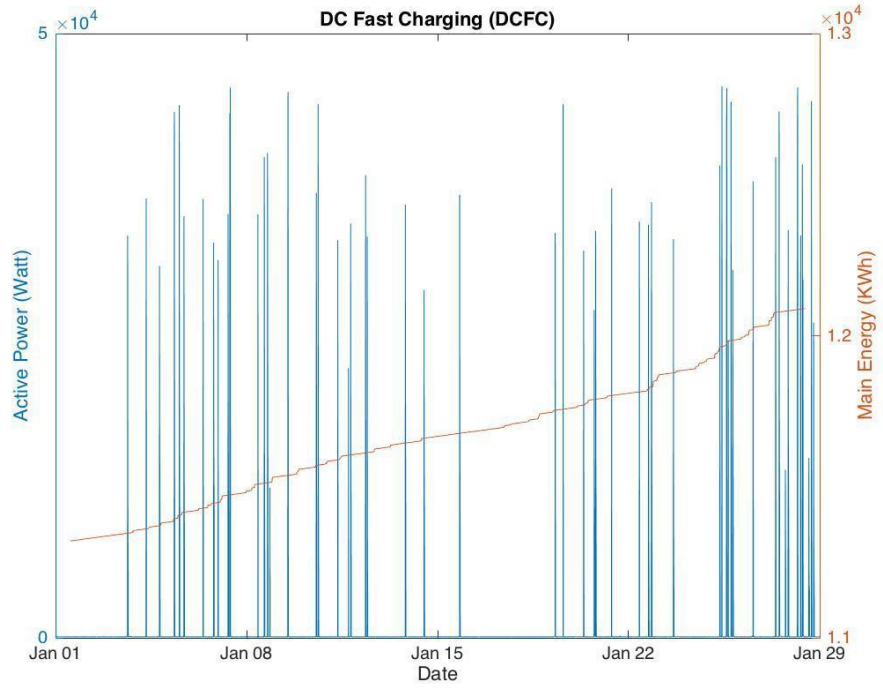


Figure 19: Power Consumption and Main Energy for DC Fast Charging for January 2015

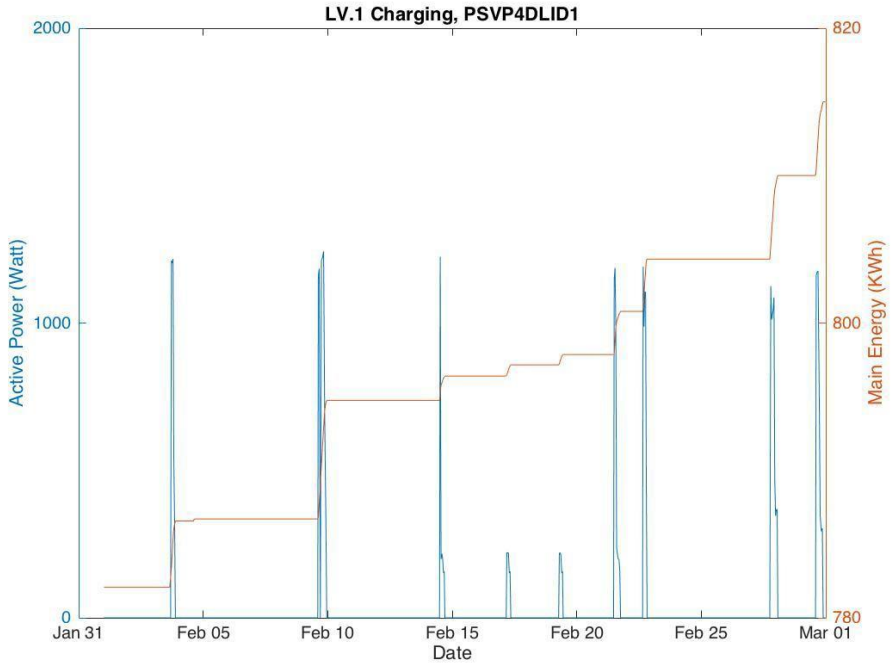


Figure 20: Power Consumption and Main Energy for Level 1 Charging for February 2016

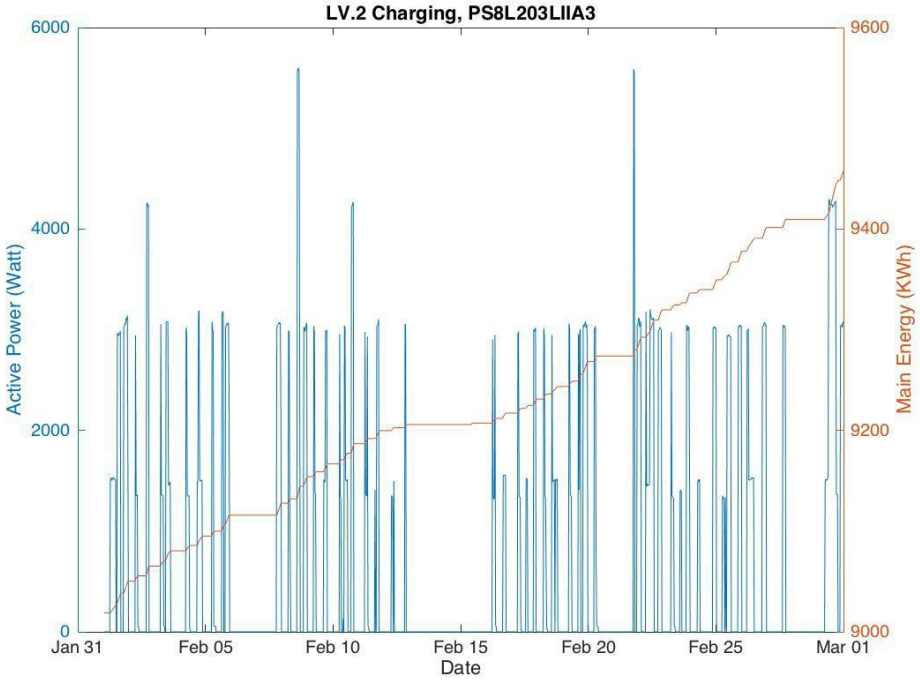


Figure 21: Power Consumption and Main Energy for Level 2 Charging for February 2016

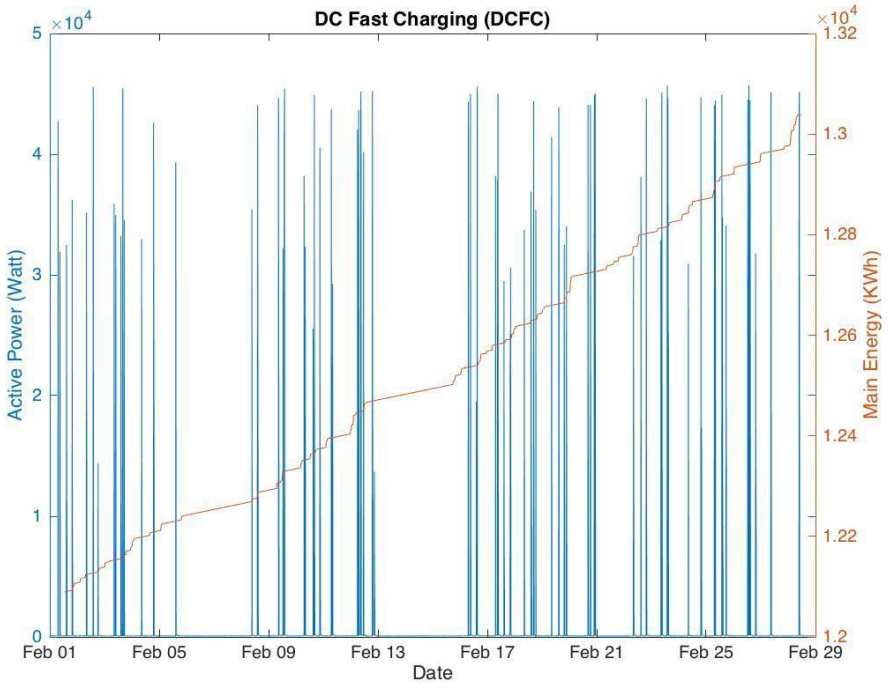


Figure 22: Power Consumption and Main Energy for DC Fast Charging for February 2016

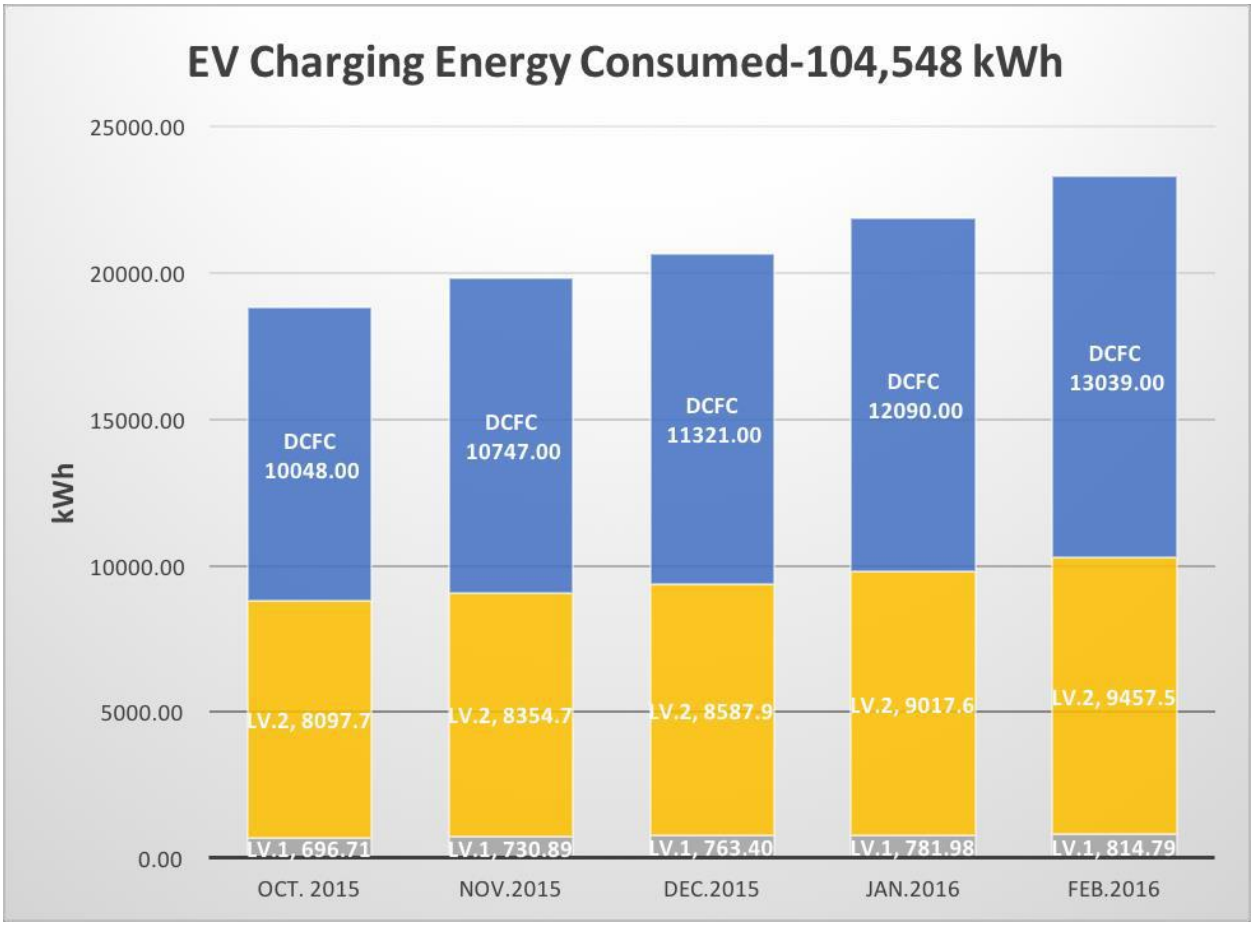


Figure 23: EV Charging Energy Consumed

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Appendix AA UCLA TPR Use Case 2

Technology Performance Report (TPR)
Use Case (Demonstration) #2
June 25, 2016

Demo/Use Case Name: Reading Power Consumption for Vehicles Connected to Chargers

Brief Description:

The purpose of this use case was to monitor and store power consumption information for a charging station. Consumption data was collected and stored at the Control Center.

Design Document Methodology (anticipated in 2011)

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. The Super Control Center and the EV Control Center at UCLA collected and stored EV charging data.

Demo responsibilities

In this demonstration, the EV project team monitored and stored power consumption information for the chargers installed for this project. Real-time and historical data was stored and collected at the SG EV Control Center. The EV project team collected the following information from EVs and chargers:

- Charger/AMI Meter ID
- Connection time stamp
- Voltage & Current
- kW

Charging stations not equipped with Smart controls or communications relied on a dedicated AMI meter connected to the charging station to transmit data. Chargers equipped with internal meters and onboard communications capability transmitted data to a 3rd party server, which was accessible to the project team. EVs connected to the charging station sent ID and time stamp data. Smart charging stations sent user profile information to the SG EV Control Center when the user activated the charger with his or her identification card.

In the SG EV Control Center, software checked the eligibility of the connected EVs and user profiles to engage the charging operation. Eligibility was determined based on an end-user profile, which contained the user account balance, charging preferences, charging history, and an EV profile which contained EV information such as make, model, and battery profile.

Once an EV was authorized, the control center sent an engage signal to the charger to activate charging. The Smart meter or equivalent sensors on the charger continuously monitored the power consumption and sent real-time data back to the SG EV Control Center through the communication gateway on an interval basis. Various time intervals were tested and an optimized value was determined based on the density of the data, communication bandwidth, and the effect of latency.

The possibility of interruptions to charging might affect the reading of power consumption. Examples include a disconnected charging cable, battery temperature, fault generated by vehicle's BMS, or a DR message requesting the charger to be turned off. Records of interruptions were event-driven and were kept in the database with timestamp information.

The SG EV Control Center provided a portal to monitor power consumption of all chargers with a graphical interface of charts and plots to analyze power consumption.

Demo steps and flow

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. EV Vitals & Scenario Data sent to Control Center
4. Control Center sends commands to Charging Station
5. Charging Station charges EV per commands
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data
7. EV informs Station when charging is complete
8. Charging Station reports results of charge to Control Center
9. Charging Station informs vehicle operator results of charging session
10. Vehicle operator removes & stores Charging Cable
11. Charging Station resets for new charging session

Planned approach

9. Monitor and Evaluate Data from EV Chargers
10. Document and report on EV charging and user habits

Final Used Methodology

Key changes in Demo design and justification

Certain data in EV vitals was currently not available and explained below. In the future, as new technologies are made available by way of hardware or software, some or all of the information might become available. If it does, we plan to collect that information. The following parameters were collected as the historical records for EV charging behaviors.

- EV ID: EV ID associated with user ID and is collected when the user uses a mobile device/smart phone to login.
- EV Battery Voltage: The UCLA EV team found that this information was currently not available readily. It is typically hidden behind the EV BMS system.
- EV battery Current: The UCLA team found that this information was currently not

available readily. It is typically hidden behind the EV BMS system.

- EV Battery State of Charge: This information was collected when the EV driver activated the charger and the EV was equipped with a SOC box (only available to Nissan Leaf and to select users.) Alternatively, the UCLA team asked EV users to enter "remaining mileage" as a base to estimate the beginning SOC and the ending SOC was estimated by the amount of energy received by the vehicle.
- EV Battery Temperature: The UCLA team found that this information was currently not available readily. It is typically hidden behind the EV BMS system.
- BMS error message – The UCLA team found that this information was currently not available readily. It is typically hidden behind the EV BMS system. The UCLA team tried to determine the process to extract this information.

As mentioned above, current SOC data was only available for Nissan Leaf and to very limited users due to the following reasons:

1. The SOC modules were a non-standard solution (i.e. it may be different for different car manufacturers) that used information obtained from on-board CAN bus communication via trial-and-error method. The official information on the format of the SOC data was currently not available.
2. The SOC data format on the CAN bus was subject to change by the EV manufacturer without EV users' knowledge. For example, the UCLA EV team was able to obtain SOC information from a Chevy Volt as reported in earlier reports but was later not possible due to a software upgrade on the vehicle.
3. It was quite troublesome for an average user to use the SOC modules to transmit the SOC data from the EV. Therefore, the amount of data collected was currently limited due to lack of participation in this experiment. The UCLA EV team looked into alternative approaches to solve this issue.
4. The TI Zigbee modules that were used for SOC application were no longer in production. Creation of additional SOC modules was very limited.
5. SOC data communication was not quite reliable. Very often, the obtained data was faulty and contained errors.

While UCLA SMERC continued to collect SOC data **independently** from one Nissan Leaf, the team adopted an alternative approach to estimate SOC. The "Remaining Mileage" was entered by the vehicle operator when enabling the charging session. The mileage information associated with the vehicle type was used to estimate the SOC and the ending SOC was estimated by the amount of energy received by the vehicle.

Lastly, due to the available temporary sensor and network connections, scenario Data (ambient temperature at EV charging stations) was also collected **independently** to study the impact of EV charging based on the change in ambient temperature.

Because of these changes, the demonstration steps were changed to the following:

1. Vehicle operators plug in the vehicle when arrived at the charging station
2. Vehicle operators use mobile application to activate a charging station
3. Control Center records initial Charging Record (starting status)

4. Control Center sends commands to Charging Station to activate the charger
5. Charging Station charges EV per commands
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
7. Control Center detects very low current are being drawn by the EV
8. Control Center records final Charging Record (ending status)
9. Control Center sends commands to end the charging session
10. Control Center informs vehicle operator results of charging session
11. Control Center resets the Charging Station for new charging session

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- 137 EV Chargers
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification"**

Progress vs. success criteria

1. Vehicle operators plug in the vehicle when arrived at the charging station - **Complete**
2. Vehicle operators use mobile application to activate a charging station - **Complete**
3. Control Center records initial Charging Record (starting status) - **Complete**
4. Control Center sends commands to Charging Station to activate the charger - **Complete**
5. Charging Station charges EV per commands - **Complete**
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data - **Complete**
7. Control Center detects very low current are being drawn by the EV - **Complete**
8. Control Center records final Charging Record (ending status) - **Complete**
9. Control Center sends commands to end the charging session - **Complete**
10. Control Center informs vehicle operator results of charging session - **Complete**
11. Control Center resets the Charging Station for new charging session - **Complete**

Observations and Results

Observations and Results

This use case discussed the design and implementation of the monitoring system. Detailed case study for the Level 1 and Level 2 chargers were conducted to show the system's real-time monitoring feasibility and all of the charging data were successfully reported to control center. Multiple parameters could be retrieved and monitored for the EVSEs at the same time.

In addition, the applications on server side and user side also supported the remote monitoring functions. The data collected in different parking infrastructure areas showed the different charging behaviors. Most EV charging energy consumption occurred at UCLA, followed by Sunset Village Fleet and Santa Monica, but the highest average energy consumption occurred at Santa Monica. It showed that the users in Santa Monica stayed longer and consumed more power per session. The data collected were important and could be further analyzed for charging optimization according to different charging demands.

Lessons Learned

- Certain data in EV vitals were currently not available. The data includes EV battery voltage, EV battery current, EV battery temperature, and Battery Management System (BMS) error messages.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected numerous data points from 136 Level 1 and Level 2 EV chargers for 5 months. These data points include the encrypted user ID, station name, start time, end time, and energy consumption.

- Additionally, the UCLA EV team collected data points from 1 Level 3 EV charger for 5 months. These data points include the start time, stop time, and energy consumption.

Data Collection Summary

UCLA EV Activbe Charging Station Status				As of 02/29/2016
Location	Voltage	Connector type	Plug Points	Network/Status
LADWP JFB Lot 6 Level 2	110 V	NEMA 5-15	4	3G
PS 9 Level 4	110 V	NEMA 5-15	4	V2G testing
PS 9 Level 6	110 V	NEMA 5-15	4	WiFi,
PS 8 level 2 North	110 V	NEMA 5-15	4	3G
PS 8 level 2 South	208 V	J1772	4	3G
PS 8 level 2 North	208 V	J1772	4	3G
PS 2 level 2	110 V	NEMA 5-15	4	3G
PS 3 level 4	110 V	NEMA 5-15	4	3G
PS 3 level 2	208V	J1772	4	3G
PS 4	208 V	J1772	8	wired
PS 2	208 V	J1772	4	3G
UCLA Medical Center	208 V	J1772	4	wired
Sunset Village Parking (fleet)	110 V	NEMA 5-15	84	wired and Wif
Nissan Level 3 Charger (PS 4)	480 VAC	CHAdeMO	1	wired and Wif

Table 1: Participating Charging Stations

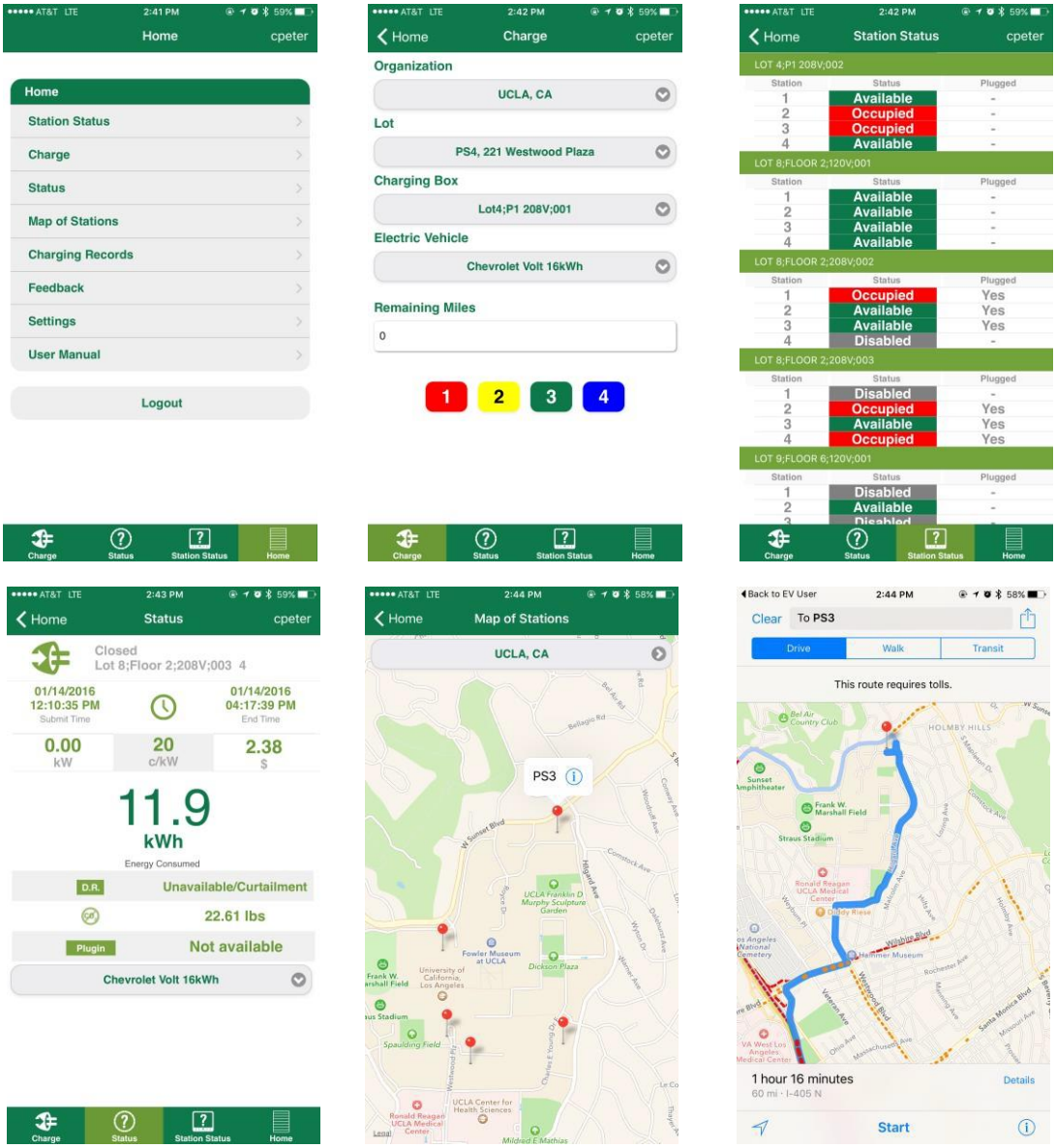
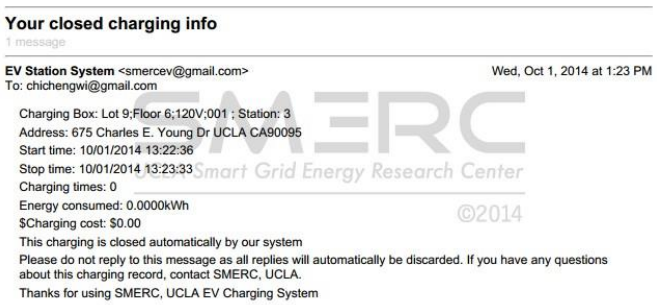


Figure 1: Screenshots from Mobile App Interface



Your closed charging info

1 message

EV Station System <smercev@gmail.com> Wed, Oct 1, 2014 at 1:23 PM
To: chichengwi@gmail.com

Charging Box: Lot 9;Floor 6;120V;001 ; Station: 3
Address: 675 Charles E. Young Dr UCLA CA90095
Start time: 10/01/2014 13:22:36
Stop time: 10/01/2014 13:23:33
Charging times: 0
Energy consumed: 0.0000kWh
$Charging cost: $0.00
This charging is closed automatically by our system
Please do not reply to this message as all replies will automatically be discarded. If you have any questions about this charging record, contact SMERC, UCLA.
Thanks for using SMERC, UCLA EV Charging System

SMERC Smart Grid Energy Research Center ©2014

Figure 2: Sample Email Sent When a Charging Session is Closed

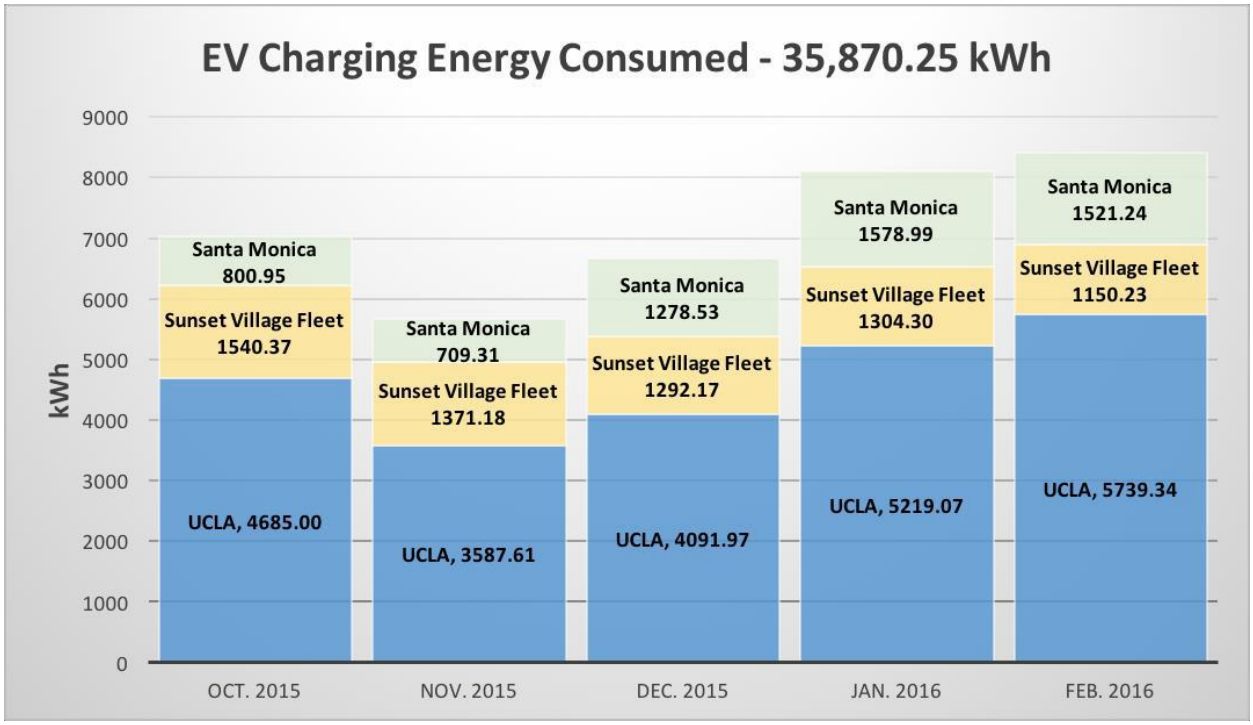


Figure 3: EV Charging Energy Consumed Oct. 2015 – Feb. 2016

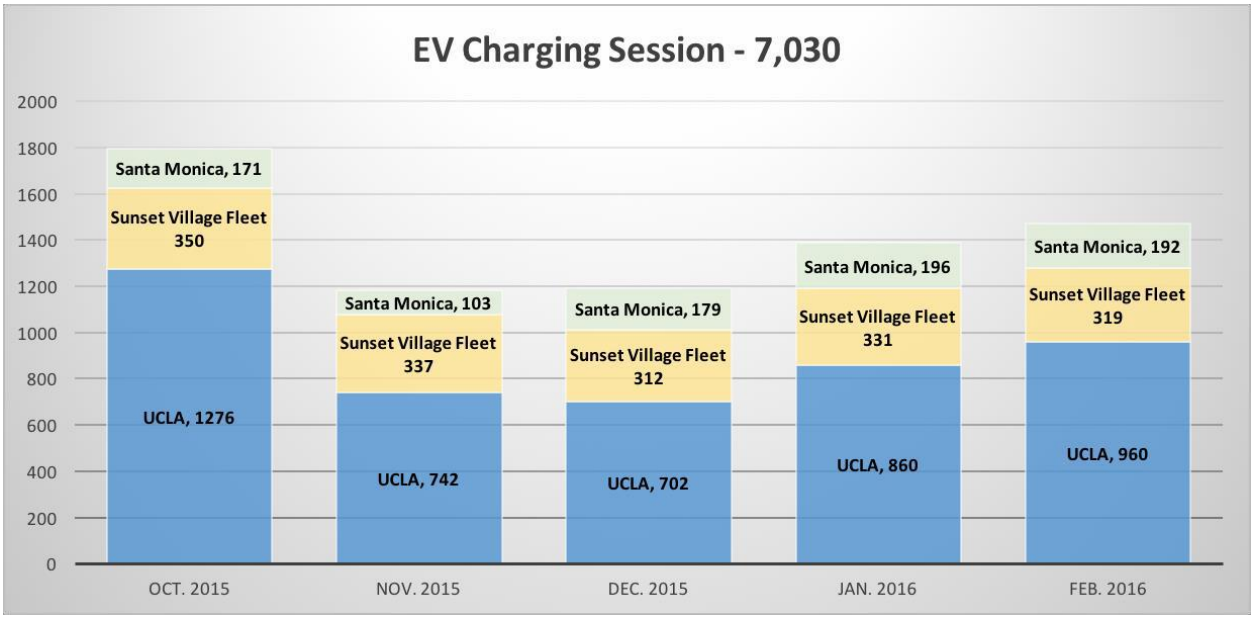


Figure 4: EV Charging Session Oct. 2015 – Feb. 2016

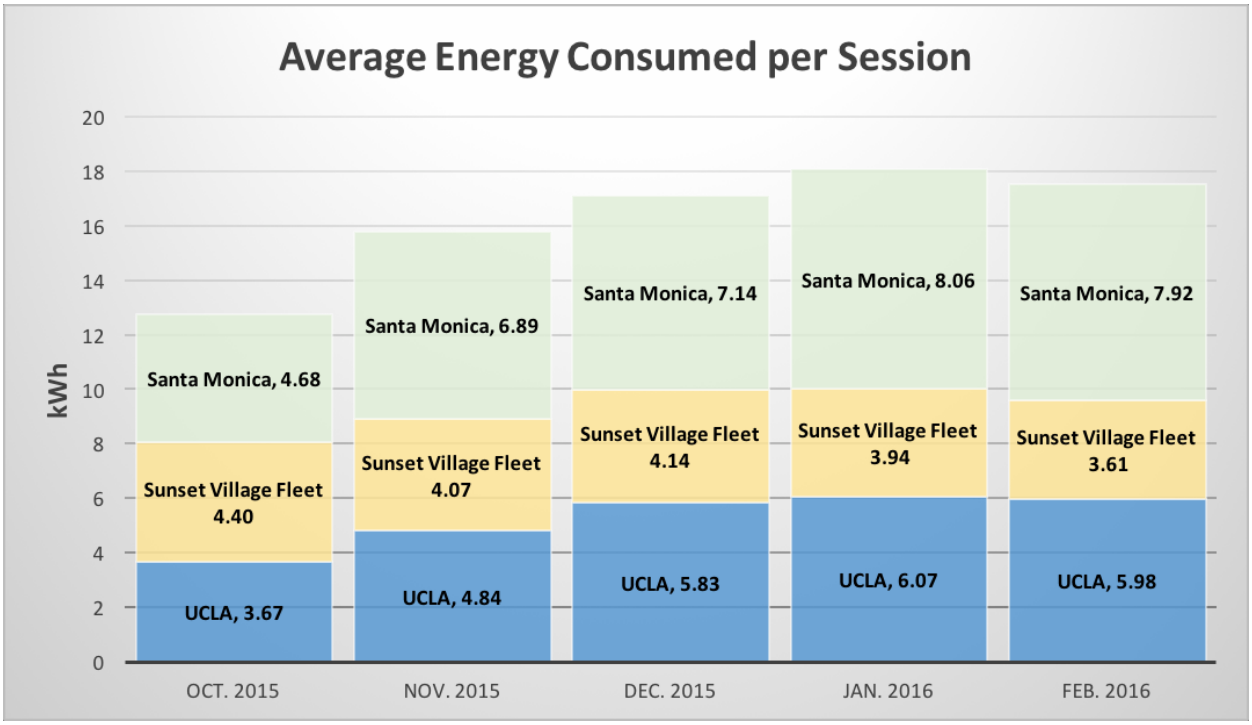


Figure 5: Average Energy Consumed per Session Oct. 2015 – Feb. 2016

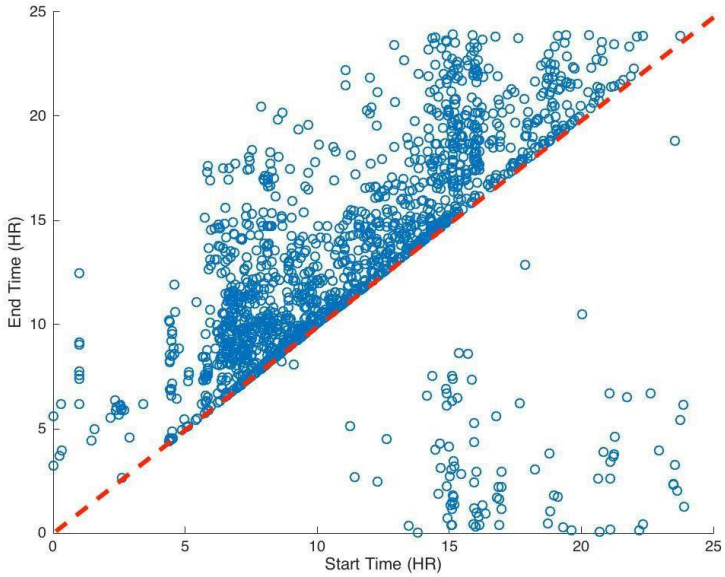


Figure 6: Monitoring of Charging Start and End Time (Oct 2015)

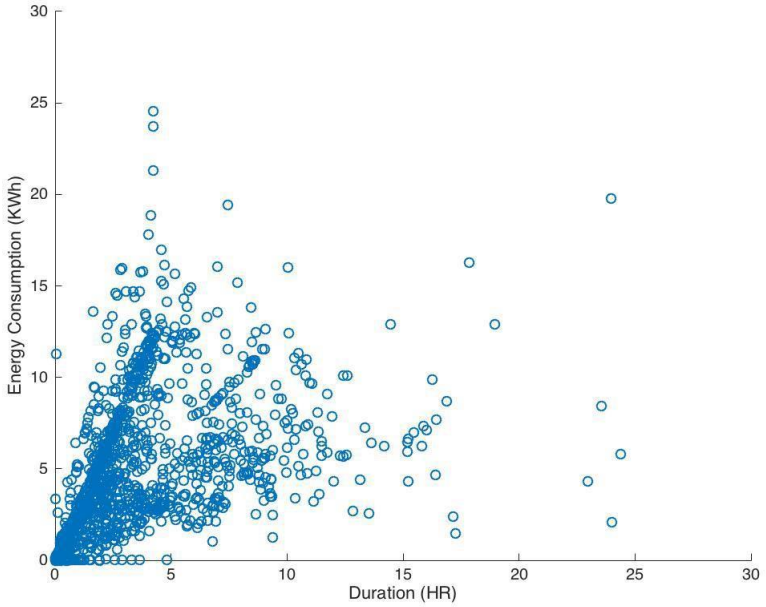


Figure 7: Monitoring of Charging Duration and Energy Consumption (Oct 2015)

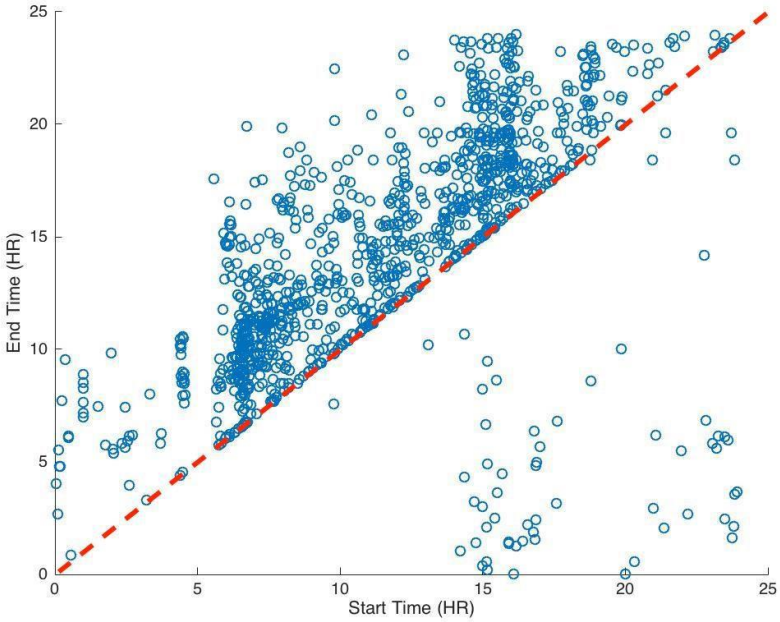


Figure 8: Monitoring of Charging Start and End Time (Nov 2015)

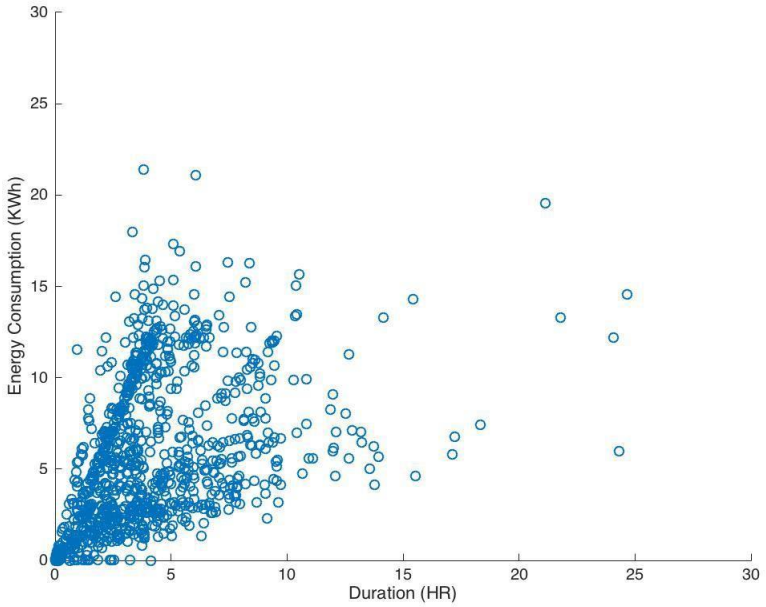


Figure 9: Monitoring of Charging Duration and Energy Consumption (Nov 2015)

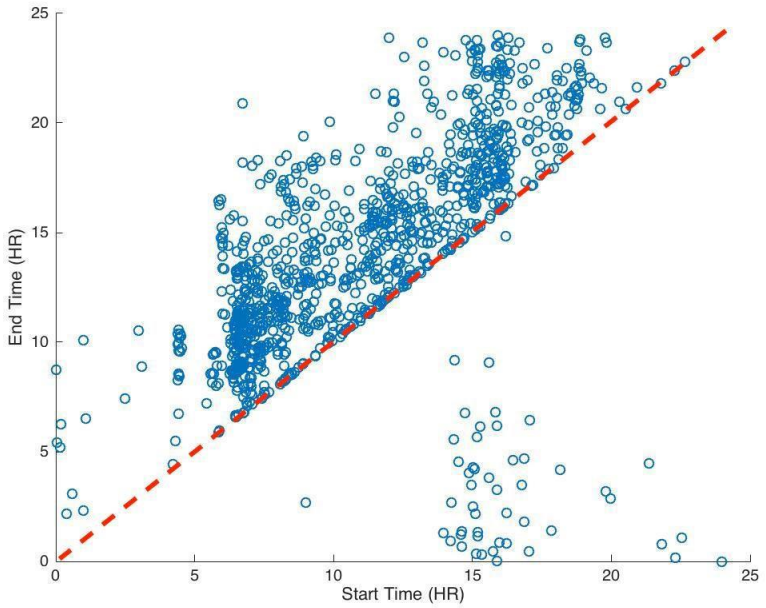


Figure 10: Monitoring of Charging Start and End Time (Dec 2015)

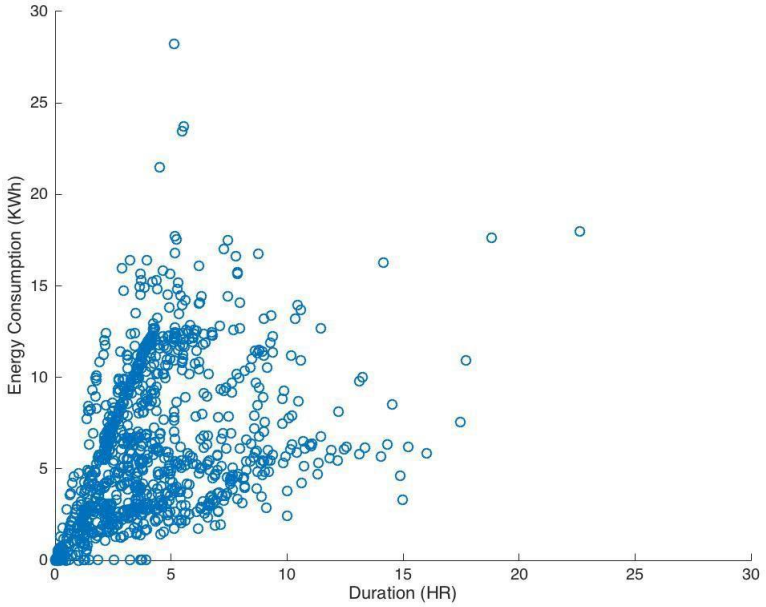


Figure 11: Monitoring of Charging Duration and Energy Consumption (Dec 2015)

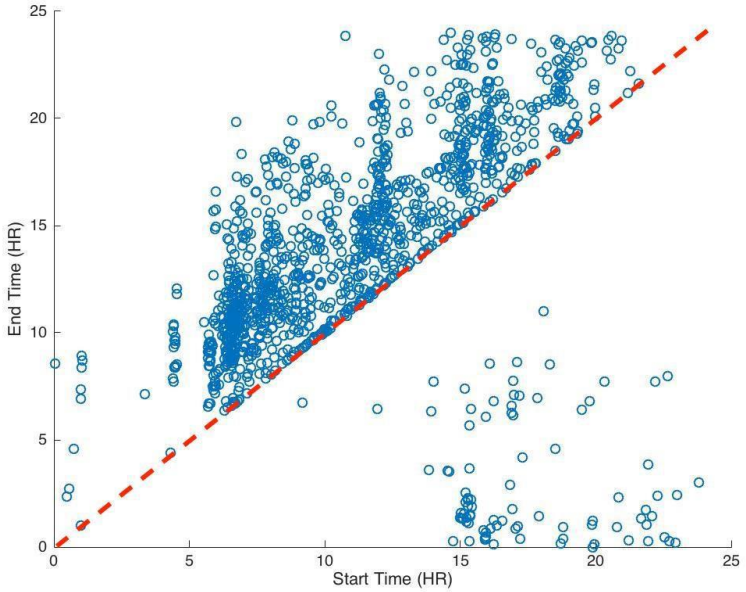


Figure 12: Monitoring of Charging Start and End Time (Jan 2016)

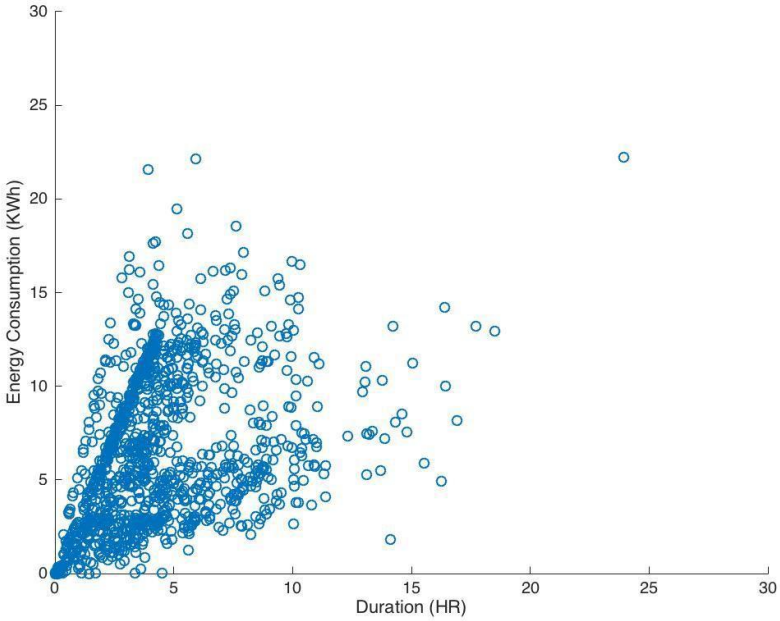


Figure 13: Monitoring of Charging Duration and Energy Consumption (Jan 2016)

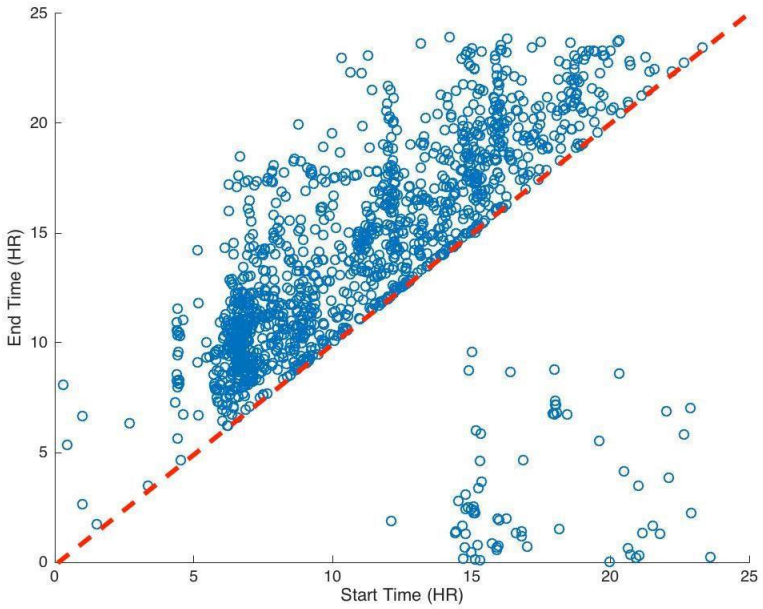


Figure 14: Monitoring of Charging Start and End Time (Feb 2016)

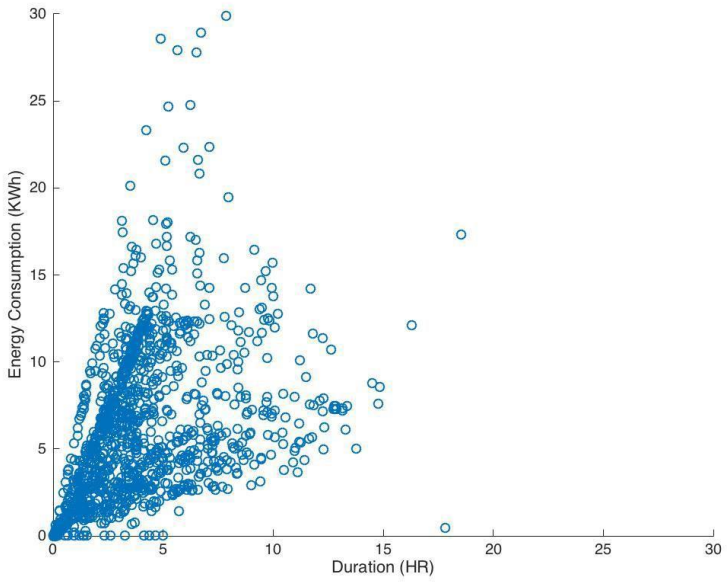


Figure 15: Monitoring of Charging Duration and Energy Consumption (Feb 2016)

List of Reports Published under this Demo

None established

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Appendix AB UCLA TPR Use Case 3

Technology Performance Report (TPR)
Use Case (Demonstration) #3
June 25, 2016

Demo/Use Case Name: Control of Chargers

Brief Description:

The purpose of this use case was to control Electric Vehicle Chargers. The Control Center would automatically manage the on/off state of the charger(s) based on various conditions collected from the system, charger, and EV.

Design Document Methodology

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. The Super Control Center sent signals out to UCLA's EV chargers with pre-defined algorithms for the Level 1 and Level 2 EV chargers. The team was able to monitor and collect data during these events.

Demo responsibilities

In this demonstration, the EV project team demonstrated charger control functions. The SG EV Control Center automatically controlled the on/off state of a charger based on various conditions from the sensor data and user profile. For chargers equipped with onboard communications and control, this was handled by a direct communication with the charger. For chargers without this capability, control was handled through a smart meter's remote switching capability. A heuristic rule engine consisted of a series of rules that will determine when to charge or backfill the vehicle's battery automatically. Factors affecting the decision logic include: transformer capacity, peak demand, time of use rate, critical peak pricing, user preferences on charging and backfill, battery profile, battery temperature, fault signal from BMS, Status of Charge (SOC) etc. The expert system determined when to turn the charger on/off and sent the control signal to the charger.

The SG EV Control Center also provided manual control of the charger through the graphical monitoring and controlling web interface.

Demo steps and flow

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. EV Vitals & Scenario Data sent to Control Center
4. Control Center sends commands to Charging Station
5. Charging Station charges EV per commands
6. EV informs Station charging is complete

7. Charging Station reports results of charge to Control Center
8. Charging Station inform operator results of charging session
9. Operator removes & stores Charging Cable
10. Charging Station resets for new charging session

Planned approach

11. Develop and demonstrate algorithms for Level 1 and Level 2 EV chargers
12. Demonstrate ability to manually control chargers
13. Monitor and evaluate data from event
14. Document and report on the control of chargers

Final Used Methodology

Key changes in Demo design and justification

As a result of UCLA research and experiment effort, UCLA SMERC's level 2 EV chargers also allowed for change of charging current on the charging stations. Therefore, the demonstration steps were changed to the following:

1. Vehicle operator plug in the vehicle when arrived at the charging station
2. Vehicle operator use mobile application to activate a charging station
3. Control Center records initial Charging Record (starting status)
4. Control Center sends commands to Charging Station to activate the charger
5. Charging Station charges EV with appropriate current based on charging scheduling algorithm
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
7. Control Center detects very little current are being drawn by the EV
8. Control Center records final Charging Record (ending status)
9. Control Center sends commands to end the charging session
10. Control Center informs vehicle operator results of charging session
11. Control Center resets the Charging Station for new charging session

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- 137 EV Chargers
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification**"

- Successfully demonstrate the ability to control EV chargers automatically via charging algorithms and manually

Progress vs. success criteria

1. Vehicle operator plug in the vehicle when arrived at the charging station - **Complete**
2. Vehicle operator use mobile application to activate a charging station - **Complete**
3. Control Center records initial Charging Record (starting status) - **Complete**
4. Control Center sends commands to Charging Station to activate the charger - **Complete**
5. Charging Station charges EV with appropriate current based on charging scheduling algorithm - **Complete**
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data - **Complete**
7. Control Center detects very little current are being drawn by the EV - **Complete**
8. Control Center records final Charging Record (ending status) - **Complete**
9. Control Center sends commands to end the charging session - **Complete**
10. Control Center informs vehicle operator results of charging session - **Complete**
11. Control Center resets the Charging Station for new charging session - **Complete**

Observations and Results

Observations and Results

From the visualization of historical charging data, both level 1 and Level 2 charging stations could be remotely controlled by the control center. For level 1 stations, the ratio of charging time in a specified time interval was determined by turning on/off for participating vehicles. Meanwhile, for level 2 stations, the variation of power consumptions was achieved by changing the power assigned to different stations with by remote control center or local control algorithms. The following issues were observed for this use case:

1) Reliability issue of frequent hardware control
2) User confusion on energy sharing strategies
3) Offline issues

Based on the analysis, both level 1 and level 2 charging algorithms were controlled effectively through EV control center and mobile applications.

Round-robin algorithm was capable of equally assigning charging time to different connected vehicles by calculating time ratio. The sample scheduling results indicated that equality in terms of charging time was guaranteed when more than 1 vehicle was connected.

Equal-sharing algorithm similarly achieved the equal allocation of energy to connected vehicles. However, the equality was guaranteed by averaging the duty-cycles for all charging sessions. Compared with the first come first serve (FCFS) scenario, equal-charging algorithm enabled

vehicles to get energy as soon as possible, even though not in the highest power rate, to avoid range anxiety. Thus, user satisfaction was improved by this algorithm.

The scheduling algorithms could be further modified to handle more complex situations and scenarios. For example, the complex demand response, regulation service operations could be involved to improve the program functionality. However, as the current disadvantages, the following issues need to be solved in the future:

- Offline issues for EVSE gateways, including both Level 1 and Level 2 boxes;
- Tesla controlling issues on level 1 charging stations, which had already been discussed in Tesla integration report, i.e. the number of consecutive switch operations by round robin algorithm was limited to 5 times.

Lessons Learned

- Ideally, instantaneous EV charger reads would be preferable as the Super Control Center and charging algorithms would have more data to make better determinations on controlling the EV Chargers. However, instantaneous reads was difficult to produce due to the sheer volume of data from all of the EV chargers. Therefore, 15 to 20 minute reads were utilized.
- Smart round-robin for level 1 and equal-sharing charging algorithm for level 2, both needed to dynamically modify the energy sharing scheduling and adjusted the charging power for different charging stations (outlets). One of the issues that was caused by frequent hardware control (adjust charging power) was that the power allocation was unstable for the existing charging sessions as new vehicles plug in and initiated charging sessions.
- Another concern from users in UCLA campus was about the understanding of the energy sharing strategies. Since both round-robin and equal-sharing algorithms involved adjusting the real-time power consumption, some users sent the EV control center with a complaint letter. However, after investigation, we found that there was a misunderstanding for these users about Round-robin algorithm, which switched charging sessions automatically.
- Certain meters may go offline due to the issues of communication network. Thus, the EVSEs affected will be out of control and the schedule algorithm cannot perform normally. Even though this issue did not happen very often, handlers in the scheduling algorithms had been added to guarantee the energy consumption schedule.

Best Practices

None established.

Results of Data Collection

The UCLA EV team collected large amount of data has been collected associated with this Use Case. The data includes an aggregate of active power usage of all EV charging stations at each of UCLA's parking structure for five months, from October 2015 to February 2016.

Data Collection Summary

UCLA EV Activbe Charging Station Status				As of 02/29/2016
Location	Voltage	Connector type	Plug Points	Network/Status
LADWP JFB Lot 6 Level 2	110 V	NEMA 5-15	4	3G
PS 9 Level 4	110 V	NEMA 5-15	4	V2G testing
PS 9 Level 6	110 V	NEMA 5-15	4	WiFi,
PS 8 level 2 North	110 V	NEMA 5-15	4	3G
PS 8 level 2 South	208 V	J1772	4	3G
PS 8 level 2 North	208 V	J1772	4	3G
PS 2 level 2	110 V	NEMA 5-15	4	3G
PS 3 level 4	110 V	NEMA 5-15	4	3G
PS 3 level 2	208V	J1772	4	3G
PS 4	208 V	J1772	8	wired
PS 2	208 V	J1772	4	3G
UCLA Medical Center	208 V	J1772	4	wired
Sunset Village Parking (fleet)	110 V	NEMA 5-15	84	wired and Wif

Table 1: Participating Charging Stations

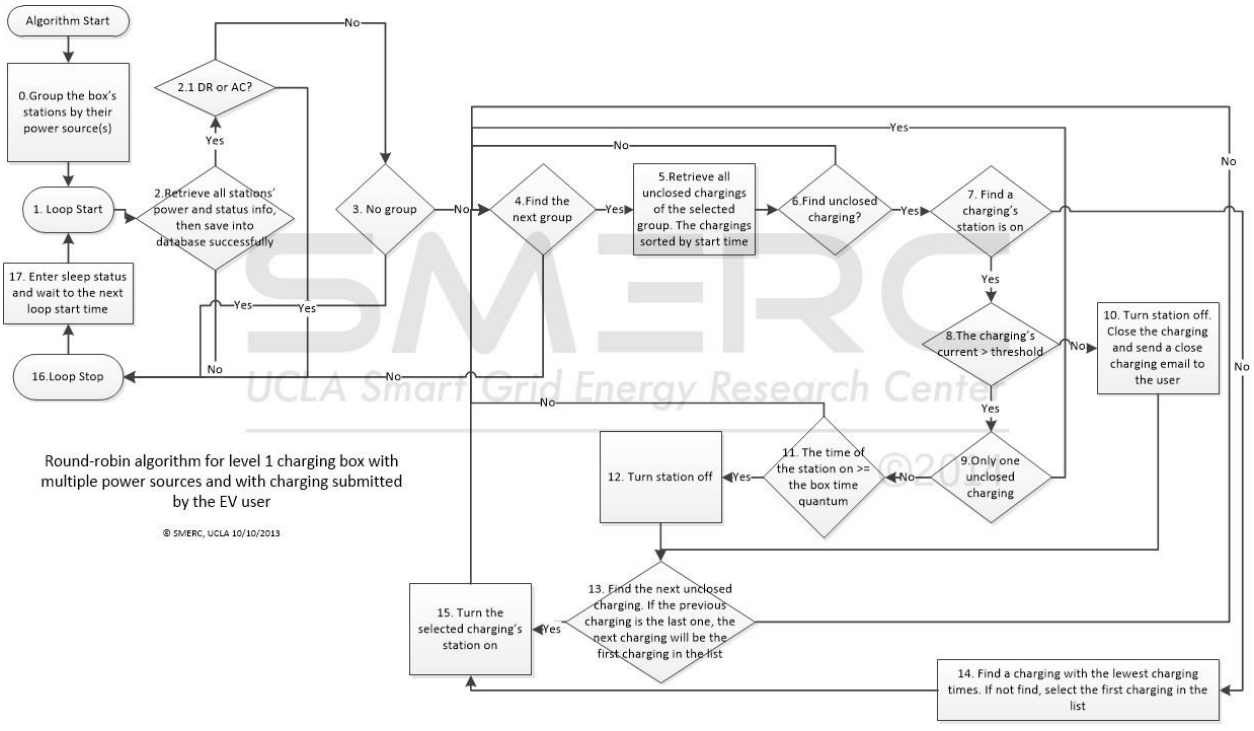


Figure 1: Smart Round Robin Control Algorithm

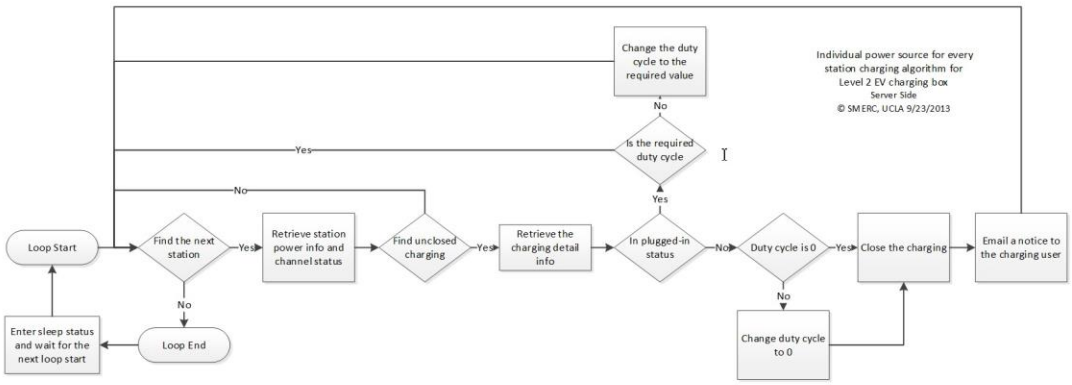


Figure 2: Level 2 Equal Sharing Algorithm

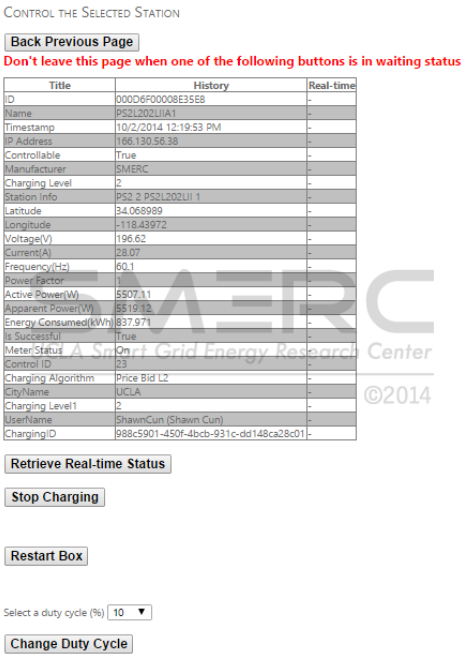


Figure 3: Suspend or Reduce Charging Current of an EV Charging Station

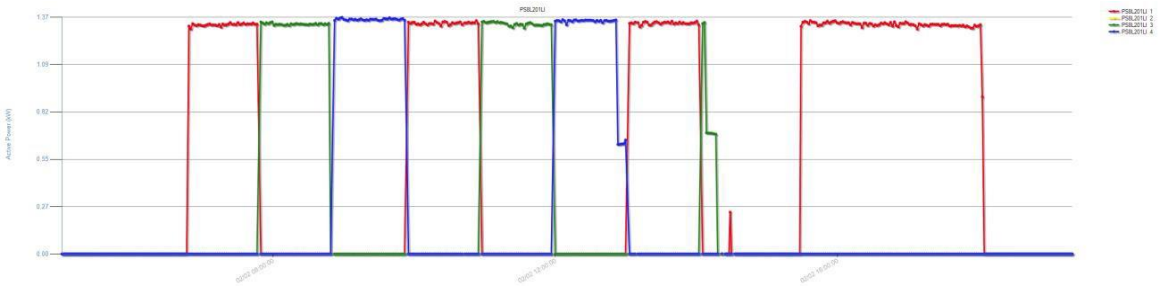


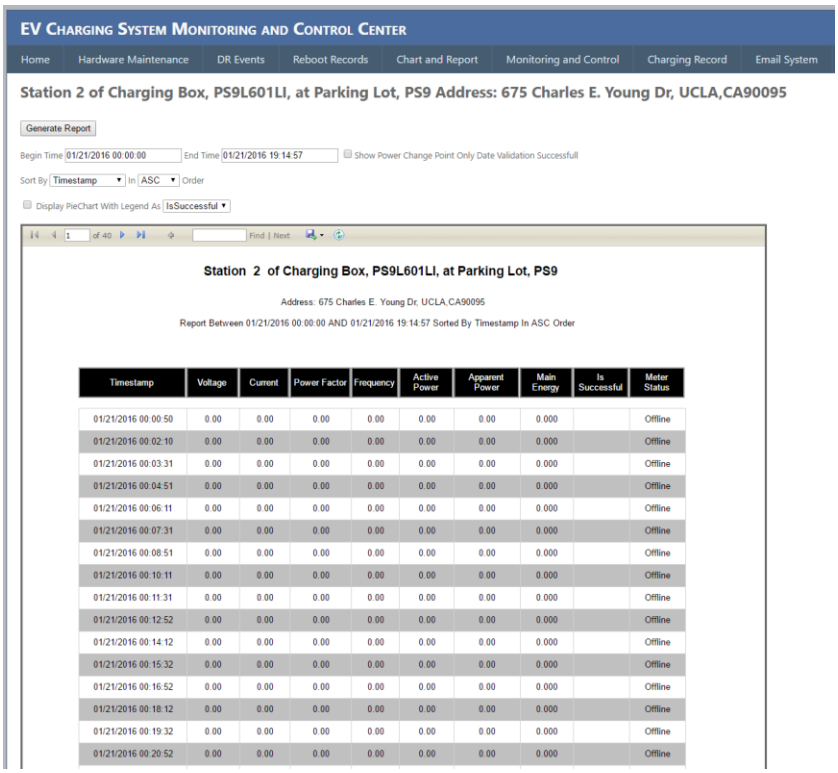
Figure 4: Control of On/Off State in Level 1 Round Robin Algorithm



Figure 5: Charging Current Control



Figure 6: Hardware Control Reliability Issues



EV Charging System Monitoring and Control Center

Home | Hardware Maintenance | DR Events | Reboot Records | Chart and Report | Monitoring and Control | Charging Record | Email System

Station 2 of Charging Box, PS9L601LI, at Parking Lot, PS9 Address: 675 Charles E. Young Dr, UCLA,CA90095

Generate Report

Begin Time 01/21/2016 00:00:00 End Time 01/21/2016 19:14:57 Show Power Change Point Only Date Validation Successfull

Sort By Timestamp In ASC Order

Display PieChart With Legend As IsSuccessful

Station 2 of Charging Box, PS9L601LI, at Parking Lot, PS9

Address: 675 Charles E. Young Dr, UCLA,CA90095

Report Between 01/21/2016 00:00:00 AND 01/21/2016 19:14:57 Sorted By Timestamp In ASC Order

Timestamp	Voltage	Current	Power Factor	Frequency	Active Power	Apparent Power	Main Energy	Is Successful	Meter Status
01/21/2016 00:00:50	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:02:10	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:03:31	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:04:51	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:06:11	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:07:31	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:08:51	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:10:11	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:11:31	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:12:52	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:14:12	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:15:32	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:16:52	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:18:12	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:19:32	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline
01/21/2016 00:20:52	0.00	0.00	0.00	0.00	0.00	0.00	0.000		Offline

Figure 7: Station Offline Issues

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

- By utilizing the ability to control chargers automatically or manually, a utility would have the ability perform load-shedding if or when necessary.

Realized Impacts and Benefits to Date

None established.

Appendix AC UCLA TPR Use Case 4

Technology Performance Report (TPR)
Use Case (Demonstration) #4
June 25, 2016

Demo/Use Case Name: Disconnect Vehicle That is Charging

Brief Description:

The purpose of this use case was to disconnect a vehicle that is charging. Connect/disconnect commands were sent from the central control center or mobile application on the user side to a specific charging station via addressable instructions.

Design Document Methodology

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. By utilizing the Super Control Center, the UCLA EV team demonstrated four different disconnects: disconnect a fully charged vehicle, the user prematurely disconnects a vehicle, EV Control Center manually disconnects a vehicle, and the user manually disconnects a vehicle via the Mobile Web Application.

Demo responsibilities

In this demonstration, EVs were disconnected mid-charge from the charging station. The SG EV Control Center received notification of the disconnection and sent a command to reset the charging station for the next EV. As with the previous Smart charging demonstrations, if the charger was equipped with Smart control and communication capability, the SG EV Control Center communicated directly with the charger. If not, monitoring and control of the charger were accomplished through the charger's dedicated AMI meter. The local gateway received the relevant commands and compiled them into new commands that were dispatched to the destination charging stations. The charging stations were connected to the local gateway through various wireless communication protocols including the AMI network and those used by the Smart chargers.

Demo steps and flow

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. EV Vitals & Scenario Data sent to Control Center
4. Control Center sends commands to Charging Station
5. Charging Station charges EV per commands
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data

7. EV informs Station charging is complete
8. Charging Station reports results of charge to Control Center
9. Charging Station inform operator results of charging session
10. EV Operator removes & stores Charging Cable
11. Charging Station resets for new charging session

Planned approach

15. Demonstrate disconnect situations on EV chargers
16. Monitor and evaluate data from EV chargers
17. Document and report on disconnects

Final Used Methodology

Key changes in Demo design and justification

Due to :

1. Vehicle operator plug in the vehicle when arrived at the charging station
2. Vehicle operator use mobile application to activate a charging station
3. Control Center records initial Charging Record (starting status)
4. Control Center sends commands to Charging Station to activate the charger
5. Charging Station charges EV with appropriate current based on charging scheduling algorithm
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
7. Control Center detects very little current are being drawn by the EV
8. Control Center records final Charging Record (ending status)
9. Control Center sends commands to end the charging session
10. Control Center informs vehicle operator results of charging session
11. Control Center resets the Charging Station for new charging session

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- Mobile Web Application
- 137 EV Chargers
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification"**
- Successfully demonstrate the disconnection of vehicles

Progress vs. success criteria

1. Vehicle operator plug in the vehicle when arrived at the charging station - **Complete**
2. Vehicle operator use mobile application to activate a charging station- **Complete**
3. Control Center records initial Charging Record (starting status) - **Complete**
4. Control Center sends commands to Charging Station to activate the charger- **Complete**
5. Charging Station charges EV with appropriate current based on charging scheduling algorithm - **Complete**
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data - **Complete**
7. Control Center detects very little current are being drawn by the EV - **Complete**
8. Control Center records final Charging Record (ending status) - **Complete**
9. Control Center sends commands to end the charging session - **Complete**
10. Control Center informs vehicle operator results of charging session - **Complete**
11. Control Center resets the Charging Station for new charging session - **Complete**

Observations and Results

Observations and Results

Among all the closed charging sessions in SMERC EV system, most of them were automatically closed by scheduling algorithms because the charging current was below the predefined threshold. On the contrary, charging sessions could be closed by the operators (users) directly through web or mobile applications. The status for the user action was stored in the database system and could be used to study the statistics of user direct controls, especially turning off actions.

Based on the vehicle disconnecting behaviors, observations were made in the following aspects:

1) Most EV users preferred not to close their charging sessions through mobile applications or web-applications. Thus, minimum input or number of operations were needed to satisfy users' preference.
2) Among the few charging sessions closed by users through their mobile applications, some of them were not normal charging sessions, because the stay duration and energy consumption were both close to 0, which meant that users may change charging locations or re-submit their charging sessions due to EVSE hardware issues.
3) In Jan. and Feb. 2016, there were no charging sessions ended by users, i.e. all sessions ended by system.

For the cases where operators removed charging cables early, the plug-in status could be used to identify this situation. In other words, the latest data point, which was recorded at a specific charging station before the charging session was closed, included a plug-in status. If this status was off, this indicated the operator unplugged their vehicle directly without closing the charging session through web or mobile application. Thus, the plug-in status before session closing could be used to identify the user behaviors and study the premature closing for charging behaviors.

According to the charging behaviors with plug-in status, the following observations were made:

1) For Level 2 chargers, quite a few charging sessions were directly and physically disconnected by users, so that the latest plug-in status was still "plug-in". The start time,

end time, and energy consumption were quite similar to those sessions closed by system. For those closed by the system, the finishing charging current was lower than the threshold, i.e. their vehicle batteries were fully charged.

2) For those charging sessions with ending plug-in status as "unknown", most of them were level 1 chargers, which did not support plug-in status.
3) The charging rate (charging power) of Level 2 chargers are faster than Level 1 chargers.

The charging behaviors, including the closing charging and unplug behaviors, indicated the user preferences over controlling their vehicles. The foundation for these functions was the capability of the smart charging system to support multiple ways to disconnect vehicles. Remote terminations by the EV server or mobile applications were both supported and the manual way of physical unplugging enabled the charging service to more flexible.

Lessons Learned

- Certain data in EV vitals were currently not available. The data included EV battery voltage, EV battery current, EV battery temperature, and Battery Management System (BMS) error messages.
- The lack of communication between the BMS and the server side algorithm makes it difficult to reduce the delay of disconnecting operations.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected numerous data points from all 137 EV chargers for 5 months, from October 2015 to February 2016. These data points include the User ID (Encrypted), Station Name, Start Time, End Time, Energy Consumption, and the type of disconnect.
- The UCLA EV team collected the station records for each case, which include the station name, time stamp, current, and active power.

Data Collection Summary

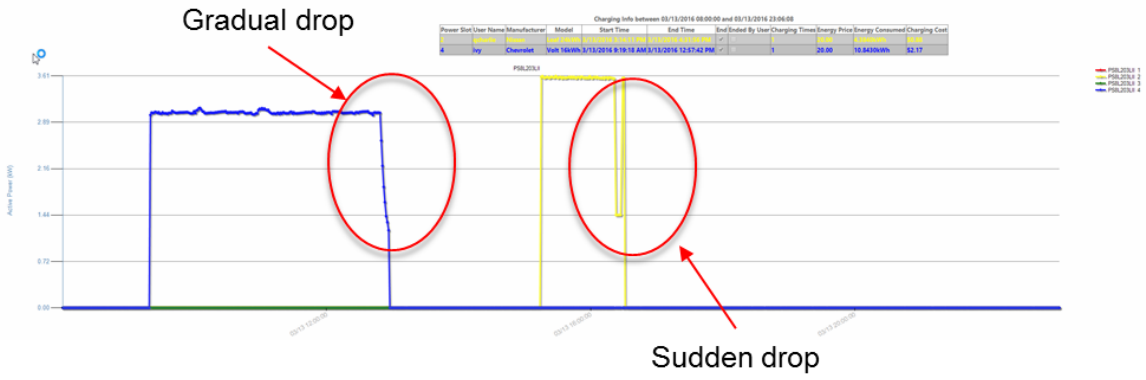


Figure 1: Disconnect Charging due to Current Drop



Figure 2: Disconnect Charging Session due to Prematurely Unplug

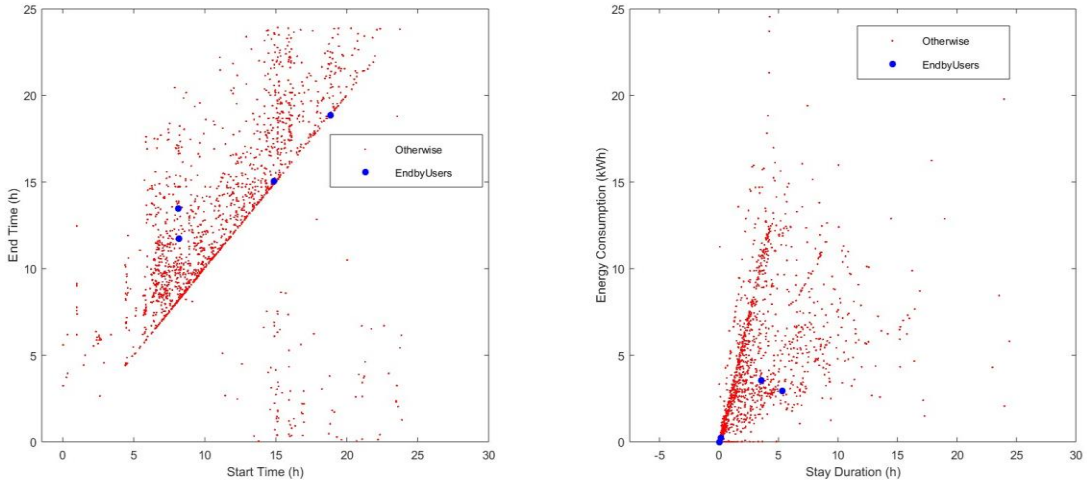


Figure 3: User Close Charging Behaviors Oct 2015

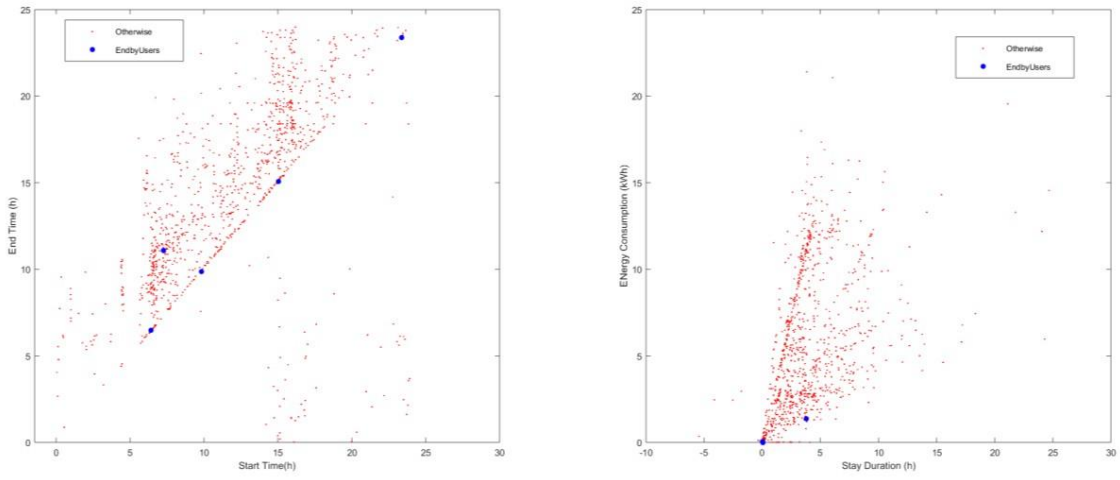


Figure 4: User Close Charging Behaviors Nov 2015

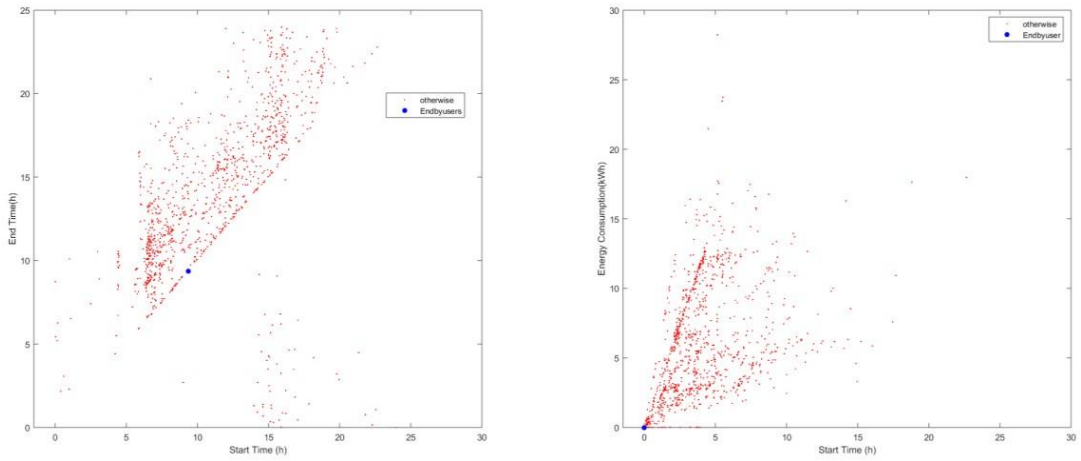


Figure 5: User Close Charging Behaviors Dec 2015

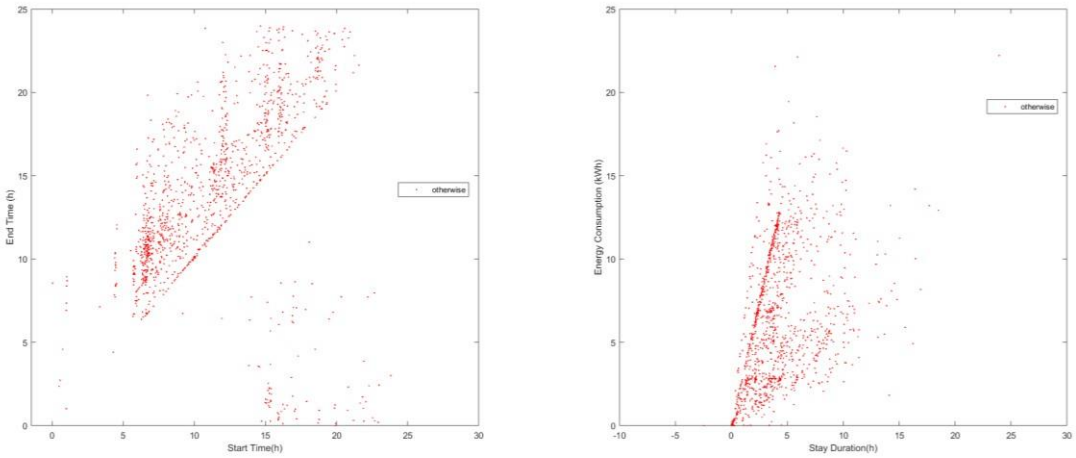


Figure 6: User Close Charging Behaviors Jan 2016

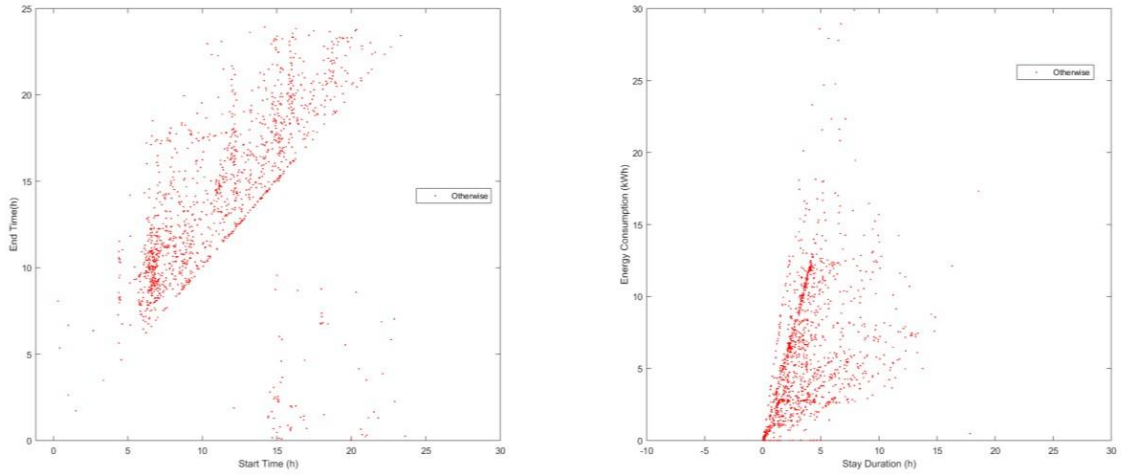


Figure 7: User Close Charging Behaviors Feb 2016

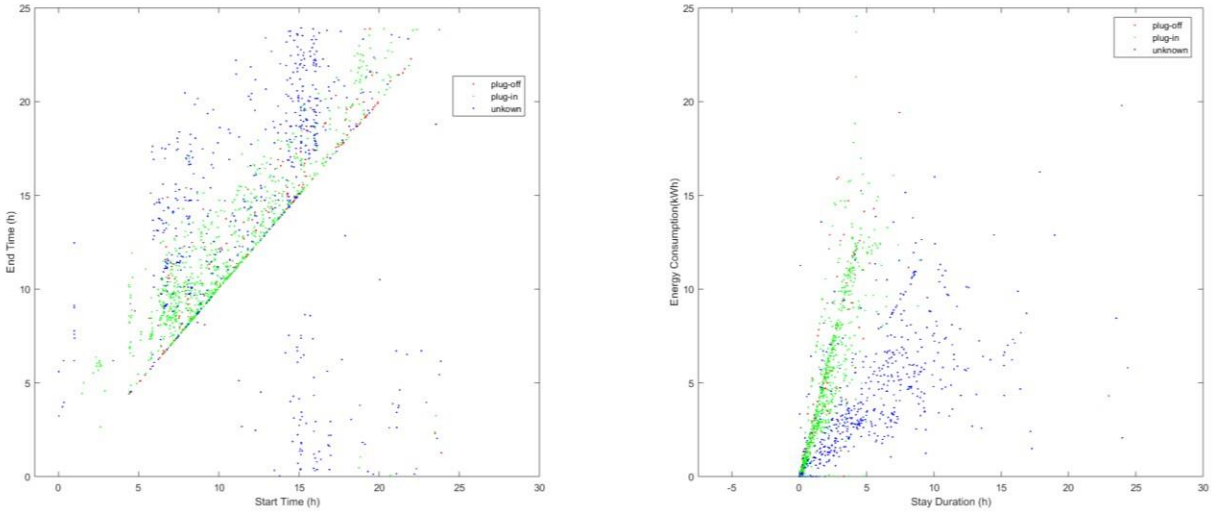


Figure 8: User Charging-Unplug Behaviors Oct 2015

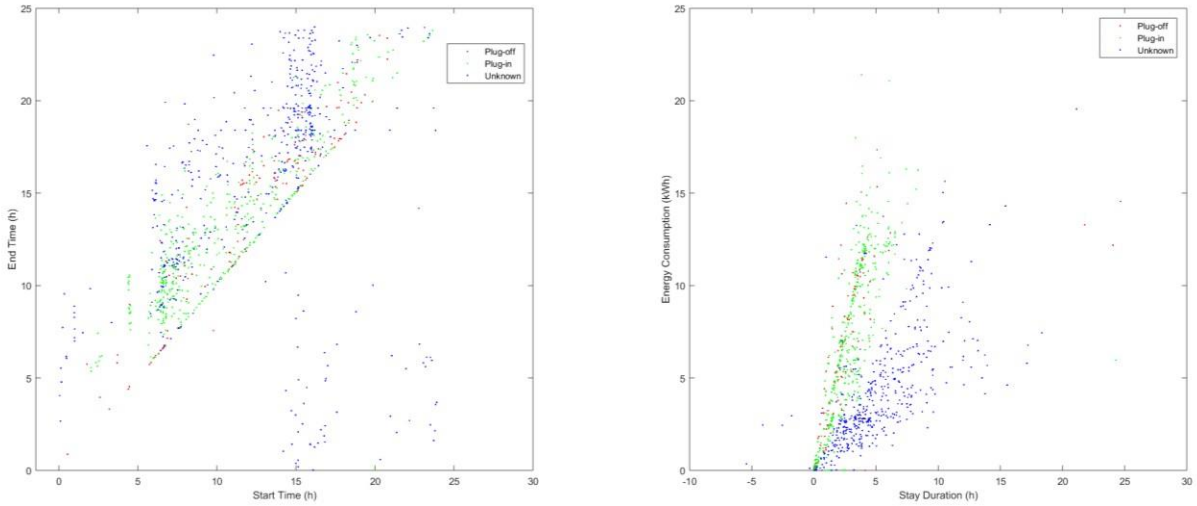


Figure 9: User Charging-Unplug Behaviors Nov 2015

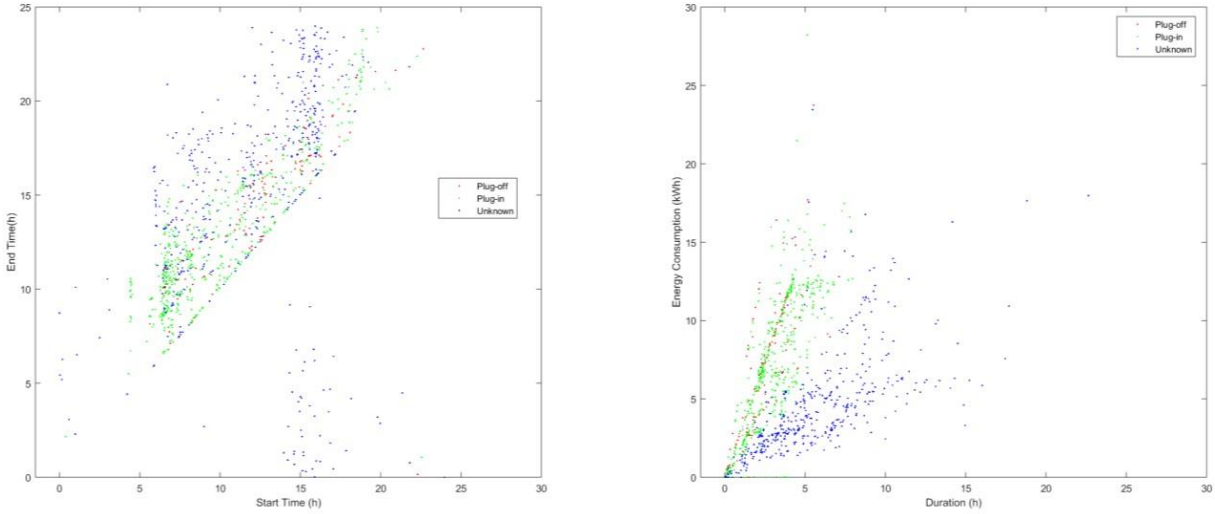


Figure 10: User Charging-Unplug Behaviors Dec 2015

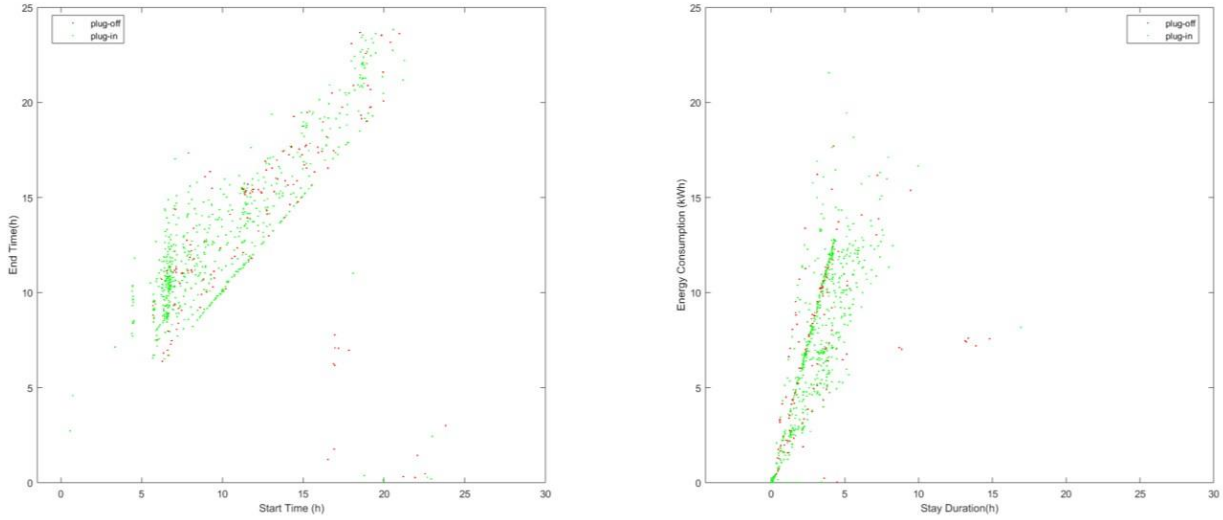


Figure 11: User Charging-Unplug Behaviors Jan 2016

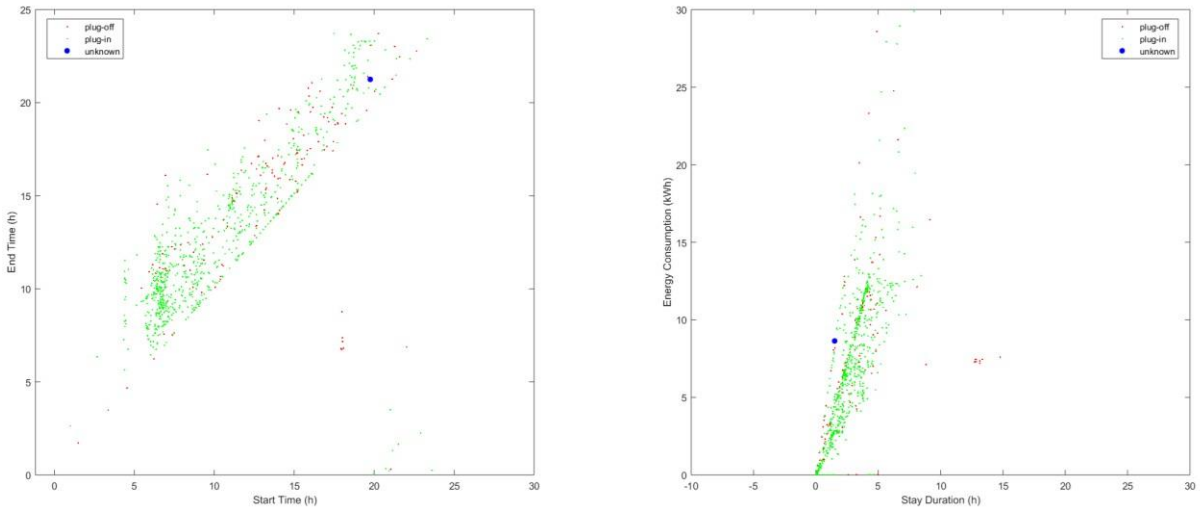


Figure 12: User Charging-Unplug Behaviors Feb 2016

	End by User	End by System	Plug-in	plug-off	unknown
UCLA	12	3264	2717	547	1276
UCLA Medical Center	0	841	658	183	0
Sunset Village	0	1649	0	0	1649

Table 1: Charging Behaviors by Organization

Location	Average starting Time	Average Stay Duration (h)	Average Remaining Mileage (mile)	Total Sessions	Total Energy Consumption (kWh)
UCLA	10:11:54 AM	3.199	6.5192	4540	2.3593e+04
Sunset Village	02:06:30 PM	5.99	0	1649	6.6582e+03
UCLA Medical Center	11:25:19 AM	2.478	0	871	5.8890e+03
JFB	Not collected	Not collected	Not collected	0	0
Total				**1358**	**7139.32**

Table 2: Energy Consumption Summary by Organization

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

- By utilizing the ability to control chargers automatically or manually, a utility would have the ability perform load-shedding if or when necessary.

Realized Impacts and Benefits to Date

None established.

Appendix AD UCLA TPR Use Case 5

Technology Performance Report (TPR)
Use Case (Demonstration) #5
June 25, 2016

Demo/Use Case Name: Smart Charging through Mobile Interface

Brief Description:

The purpose of this use case was to display the status of all chargers and to indicate whether or not the charger is charging. To fulfill this task, a control and monitoring center monitored all the charging behaviors at UCLA campus. In addition, a data collection service and a database system were developed to periodically retrieve the charging requests and store the status.

Design Document Methodology

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. Additionally, the team developed an iOS application and an Android application that allows users to manage their charging sessions, display real-time availability and location of EV chargers, and receive messages and alerts regarding battery status and backfill.
The UCLA EV team demonstrated five different scenarios for pricing algorithms in order to save charging costs for EV users. The five scenarios are as follows: Level I Price-bid algorithm, Level II Price-bid Algorithm, Historical Data for Price-based charging Algorithm, User Price Preferences, and Priority Charging.

Demo responsibilities

In this demonstration, the UCLA EV team demonstrated the use of mobile devices to control EV battery charging and backfill operations. One of the salient features of the Service Gateway software system was that it provided an open architecture and web-based interface for ease of integration with multiple protocol and platforms. The user could access all the monitoring and controlling functions through multiple channels of communications. One of the most common applications to be utilized for this purpose was the web browser. In addition to using the web browser to monitor and control the charger, the software also provided open API and interfaces for mobile application developers to create customized applications.

The UCLA EV project team developed and implemented the web interface and API interface mentioned above, as well as develop applications for iPhone OS and Android OS mobile devices. The functions provided on the mobile devices include:

- Display maps of available charging stations nearby (location-based service)

- Monitor status of charge (percentage, time to full charge, remaining miles)
- Set preference for charging (economic, fast, acceptable rates, etc.)
- Receive alerts on battery status (low battery alert)
- Receive message to opt for battery backfill
- Set preference for backfill (allowable discharge percentage, time of backfill, etc.)

Demo steps and flow

There were 3 main items for this demonstration:

1. Search for Charging Station
   a. User selects **Search** Option from Mobile App.
   b. Search defaults to user's location or allows user to select new location
   c. Map shows available Charging Stations based on selected location
   d. User selects desired Charging Station
   e. Map displays driving directions to selected Charging Station
2. Monitor Charging Progress
   a. User selects **Alert** Option from Mobile App
   b. User enters Charging Station ID
      i. EV must be connected to Charging Station
   c. User preferences are displayed for verification (and changes)
   d. Monitoring process begins (based on preferences)
   e. Monitoring process stops when charging session is terminated or user logs out of system
3. Set up Charging Preferences
   a. User selects **Preference** Option from Mobile App
   b. User views and updates stored user preferences
   c. User saves changes (or cancel to exit without saving)

Planned approach

18. Develop Mobile App for iOS and Android devices
19. Monitor and evaluate data from Mobile App
20. Document and report on Smart Charging through a Mobile Interface

Final Used Methodology

Key changes in Demo design and justification

Because Vehicle-2-Grid (V2G) operations were not feasible for the regular EV users, V2G operations were now performed in the Control Center instead of the general user's mobile device. However, a Control Center operator might still access the functions of the Control Center through mobile devices. Based on the research and observation, the Demonstration flow was changed to the following:

1. Search for Charging Station
   a. User selects "**Map of Available Stations**" Option from Mobile App or web interface.
   b. Allows user to select location from participating locations
   c. Map shows available Charging Stations based on selected location

d. User selects desired Charging Station
e. Map displays driving directions to selected Charging Station

2. Monitor Charging Progress
   a. User selects "Map of Available Stations" Option from Mobile App or web interface.
   b. Allows user to select location from participating locations
   c. Map shows available Charging Stations based on selected location
   d. User selects desired Charging Station
   e. Map displays driving directions to selected Charging Station
3. Set up Charging Preferences
   a. User specifies preference when he/she starts a charging session from Mobile App.
   b. User views and updates stored user preferences
   c. User start the charging session with specified preference.

Technologies Deployed

List of systems/equipment deployment, tie back to intro tables

- Super Control Center
- EV Control Center
- 137 EV Chargers
- UCLA EV Mobile Application
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification"**

Progress vs. success criteria

1. Search for Charging Station
   a. User selects "**Map of Available Stations**" Option from Mobile App or web interface - **Complete**
   b. Allows user to select location from participating locations - **Complete**
   c. Map shows available Charging Stations based on selected location - **Complete**
   d. User selects desired Charging Station - **Complete**
   e. Map displays driving directions to selected Charging Station - **Complete**
2. Monitor Charging Progress
   a. User selects "Map of Available Stations" Option from Mobile App or web interface - **Complete**
   b. Allows user to select location from participating locations - **Complete**
   c. Map shows available Charging Stations based on selected location - **Complete**
   d. User selects desired Charging Station - **Complete**
   e. Map displays driving directions to selected Charging Station - **Complete**
3. Set up Charging Preferences
   a. User specifies preference when he/she starts a charging session from Mobile App -

Complete

b. User views and updates stored user preferences - **Complete**
c. User start the charging session with specified preference - **Complete**

Observations and Results

Observations and Results

Smart charging algorithms took many factors into considerations to improve the user experiences. However, different configurations had different impacts on the system performance and users' experiences. According to the observations, the best practices should include the following:

1. Minimum user input
2. Straight-forward display of the energy consumption values
3. Minimum complexity for participating users to understand

Based on the above analysis, the advantage of smart charging algorithms with user preferences, especially price-based algorithms, was obvious, because users' preferences could be captured by the mobile applications. Navigation services and station status page provided additional conveniences for users to find available EVSE in a timely manner. The requests and preferences were then considered in the scheduling algorithms, which optimized the energy consumption and reduced the energy cost for participating users.

The analyses for the price-based scheduling algorithms revealed that:

1) Variations of price preferences among users towards energy prices existed, which could be inferred from the box plot of historical price selections;
2) Price selection and the urgency of charging schedules were related;
3) Strategy space for EV users in the "bid-game" was large which meant different strategies could result in quite different values of energy consumption and costs. Users were able to avoid high price time interval by shifting the energy demand lower-price regions.

However, the close-form optimization, which included the direct relations between energy consumption values and energy prices, was still needed to derive the most efficient solutions. For instance, in the specific locations, the relationship between energy demand and energy prices could be optimized to fully represent the supply and demand. Accordingly, prices under this pricing paradigm could be used directly in the optimization program with the objective to minimize the total energy cost by shifting energy consumptions from high-price regions to lower-price regions.

Lessons Learned

Future research will need to be focused on the optimization of pricing strategies and the energy management algorithms. More survey on user preferences on energy price, charging control strategies, and mobile application interfaces should be conducted to better understand users' energy consumption behaviors.

Best Practices

Based on the above findings, the UCLA EV team replaced the smart charging algorithms with price preferences and time schedule preferences with the round robin algorithm for Level I and equal-charging algorithms for Level II.

Results of Data Collection

- The UCLA EV team collected user charging records and EV charger records from 5 different scenarios: Level I Price-bid algorithm, Level II Price-bid Algorithm, Historical Data for Price-based charging Algorithm, User Price Preferences, and Priority Charging.
- The user charging record data included encrypted User IDs, Energy Price, Station Name, Start Time, End Time, and Energy Consumption. The EV charger record data includes the Station Name, Timestamp, Current Energy Consumption, and Total Active Power.

Data Collection Summary

UCLA EV Activbe Charging Station Status				As of 02/29/2016
Location	Voltage	Connector type	Plug Points	Network/Status
LADWP JFB Lot 6 Level 2	110 V	NEMA 5-15	4	3G
PS 9 Level 4	110 V	NEMA 5-15	4	V2G testing
PS 9 Level 6	110 V	NEMA 5-15	4	WiFi,
PS 8 level 2 North	110 V	NEMA 5-15	4	3G
PS 8 level 2 South	208 V	J1772	4	3G
PS 8 level 2 North	208 V	J1772	4	3G
PS 2 level 2	110 V	NEMA 5-15	4	3G
PS 3 level 4	110 V	NEMA 5-15	4	3G
PS 3 level 2	208V	J1772	4	3G
PS 4	208 V	J1772	8	wired
PS 2	208 V	J1772	4	3G
UCLA Medical Center	208 V	J1772	4	wired
Sunset Village Parking (fleet)	110 V	NEMA 5-15	84	wired and Wif

Table 1: Participating Charging Stations

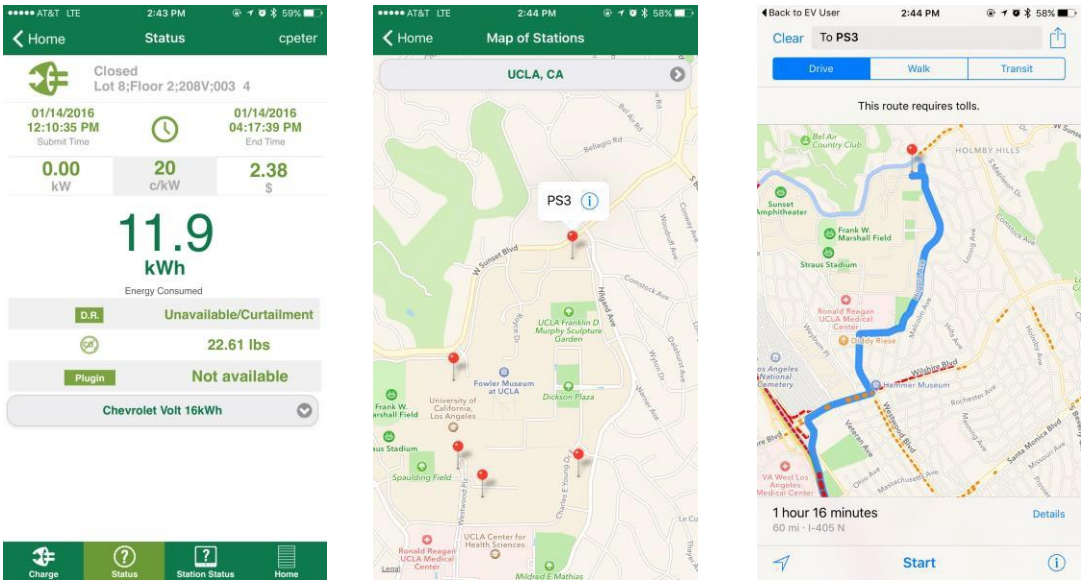


Figure 1: Navigation Feature on Smart Charging Applications on iOS

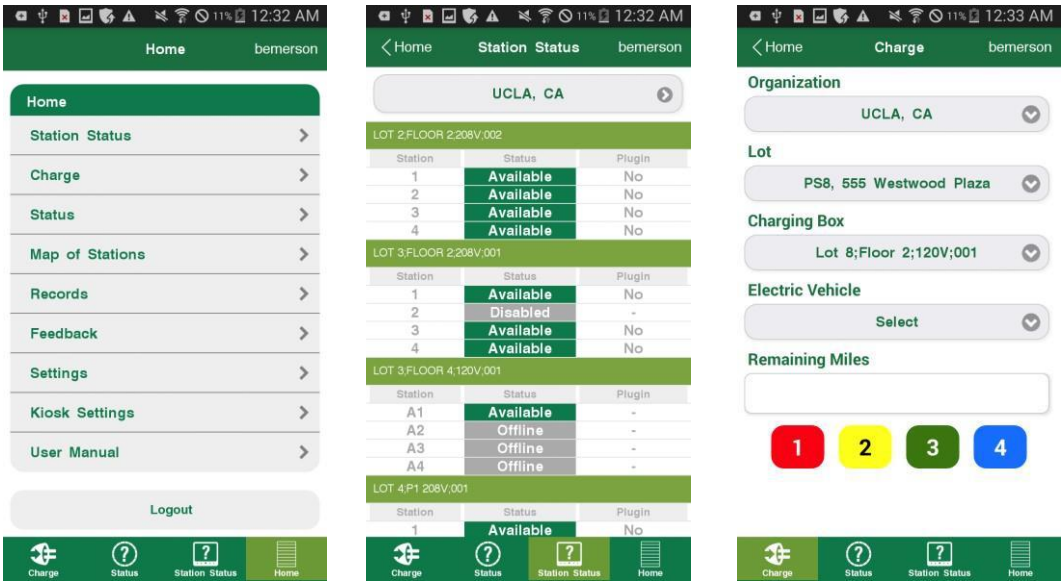


Figure 2: Smart Charging Mobile Application on Android

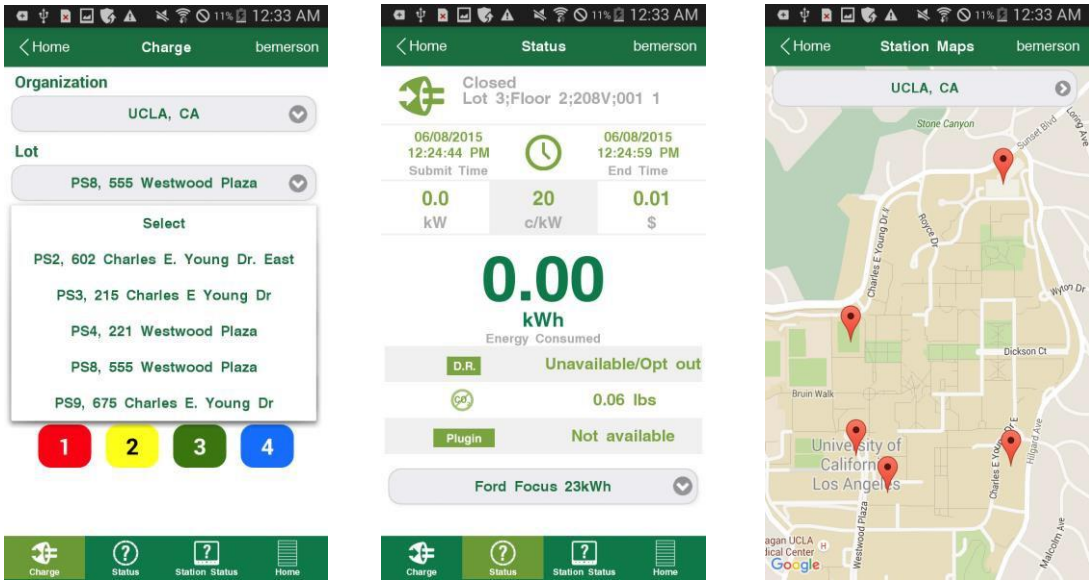
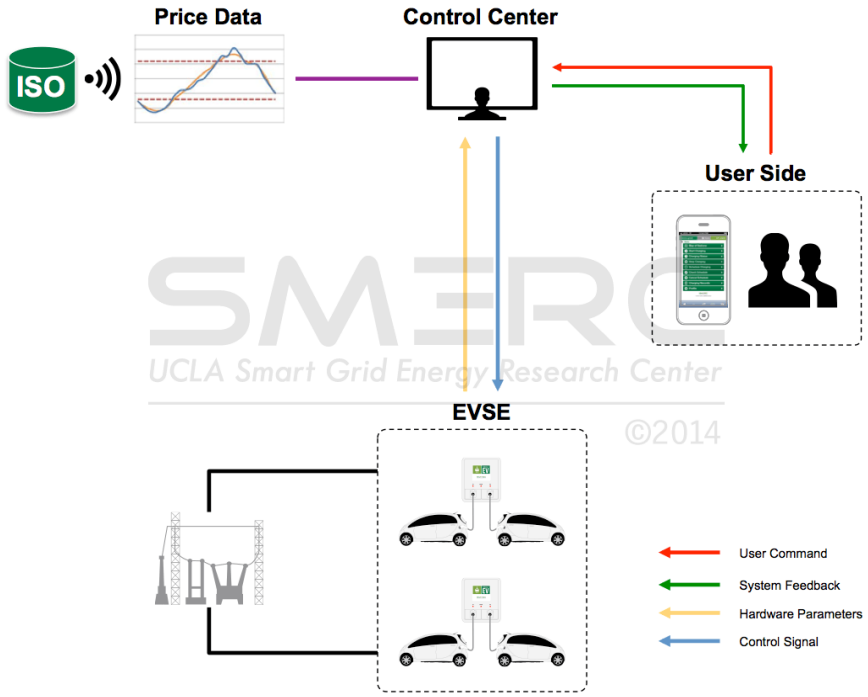


Figure 3: Navigation Feature on Smart Charging Applications on Android



SMERC
UCLA Smart Grid Energy Research Center
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Figure 4: Overview of Price-based Charging System

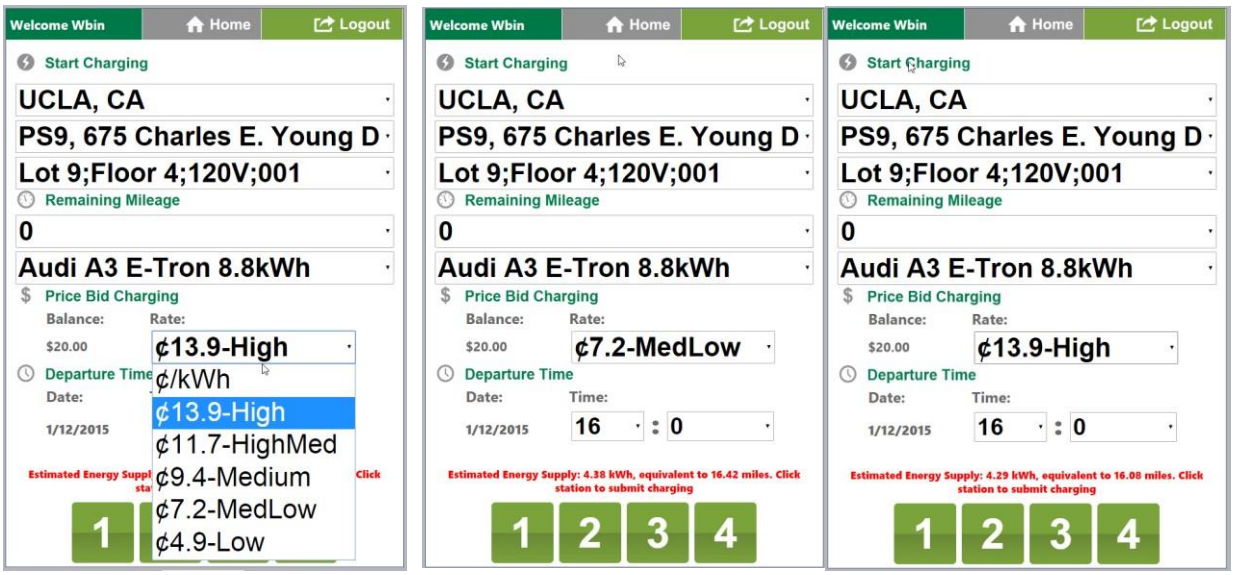


Figure 5: Interface Design for Price-based Algorithm

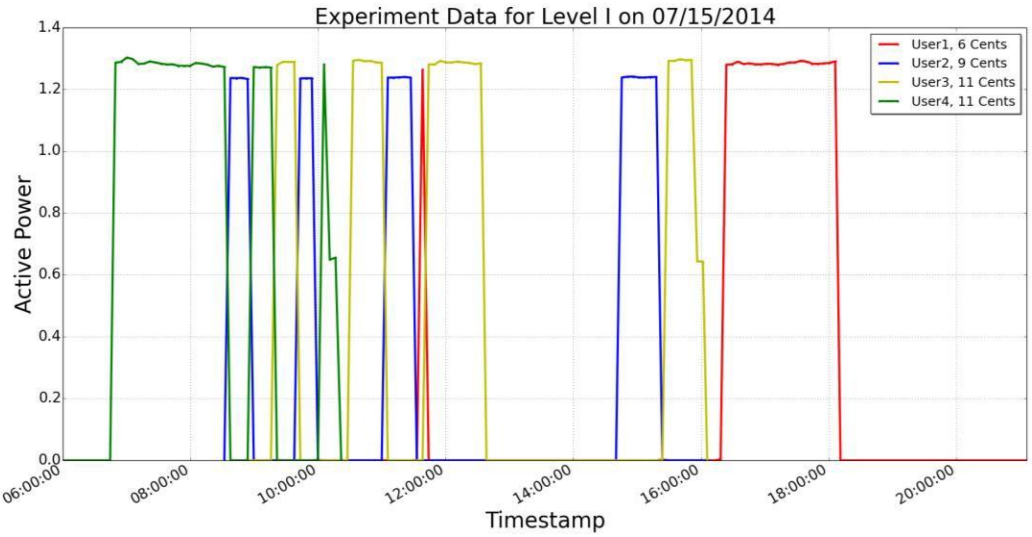


Figure 6: Scheduling Results for Level 1 Price-Bid Algorithm

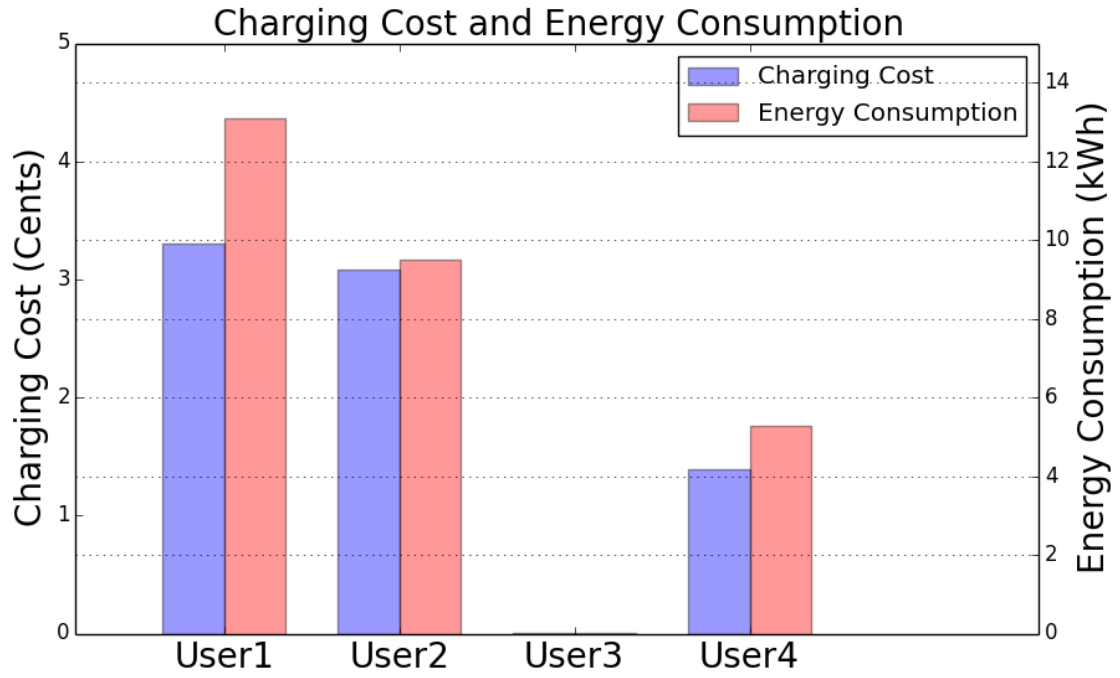


Figure 7: Cost Comparison for Level 1 Price-Bid Algorithm

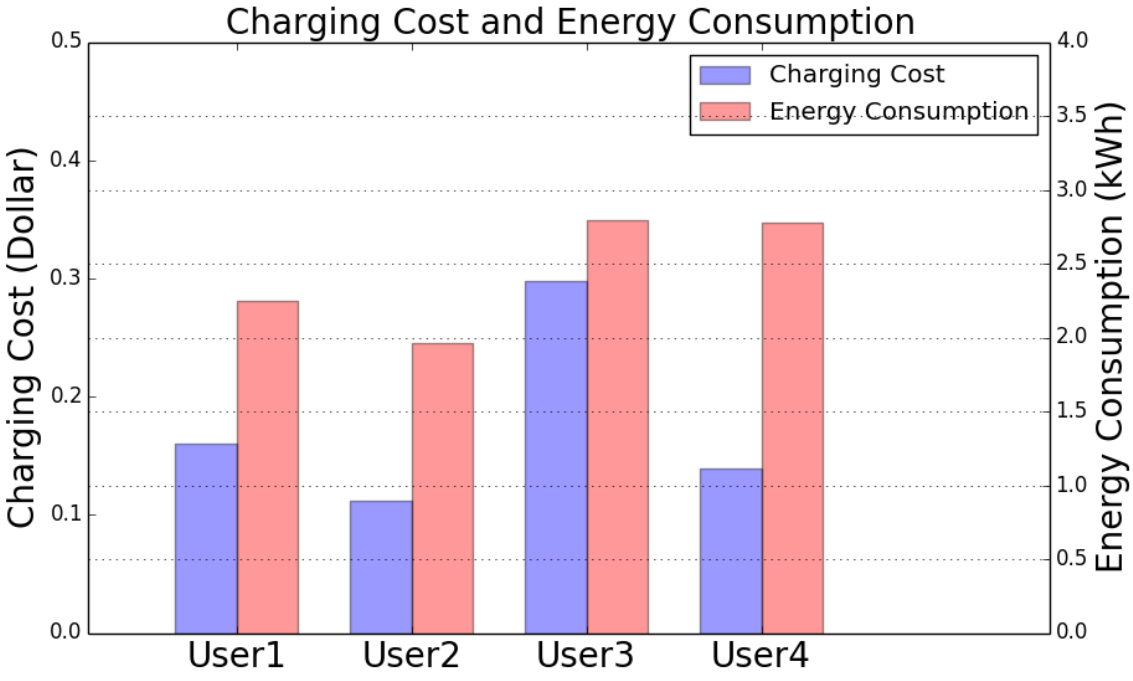


Figure 8: Cost Comparison for Level 2 Price-Bid Algorithm

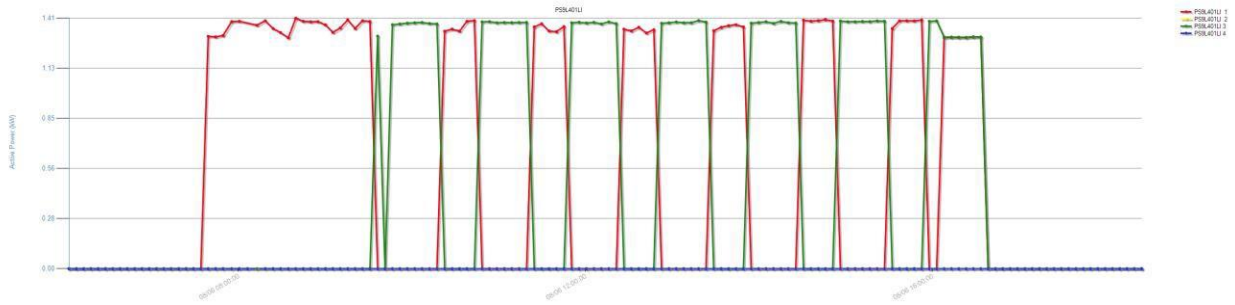


Figure 9: Experiment Results PS9L401LI on 08/06/2014

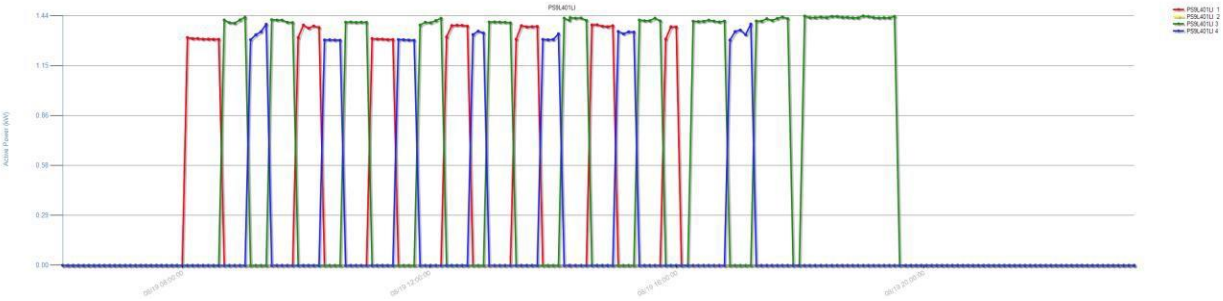


Figure 10: Experiment Results PS9L401LI on 08/19/2014

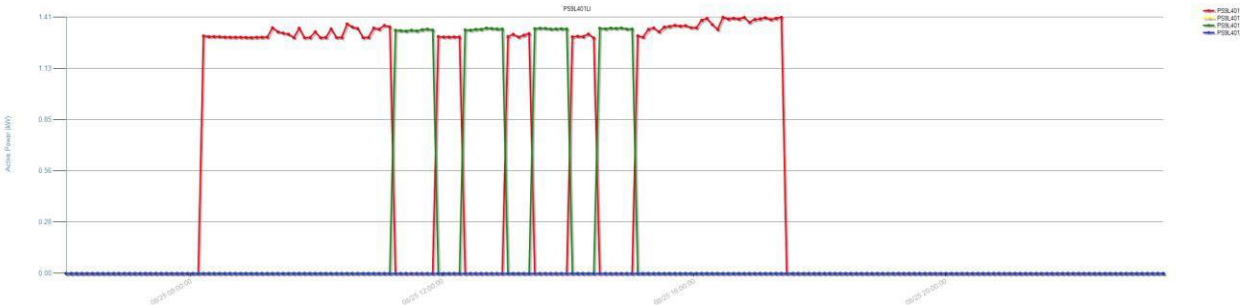


Figure 11: Experiment Results PS9L401LI on 08/25/2014

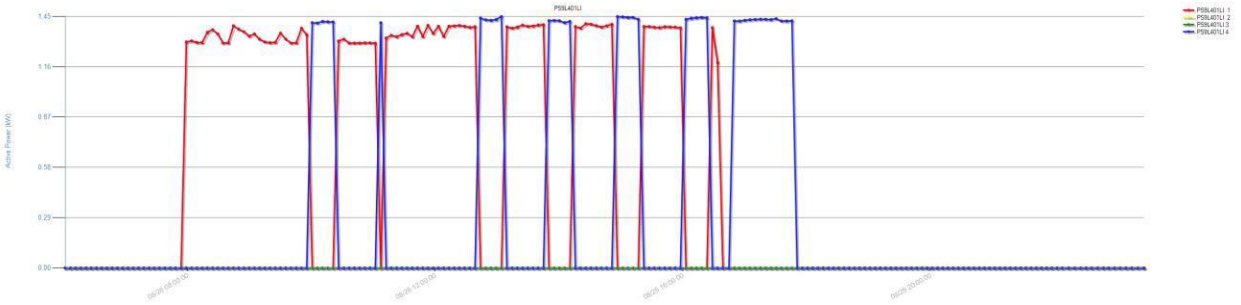


Figure 12: Experiment Results PS9L401LI on 08/26/2014



Figure 13: Experiment Results PS2L202LII on 07/28/2014

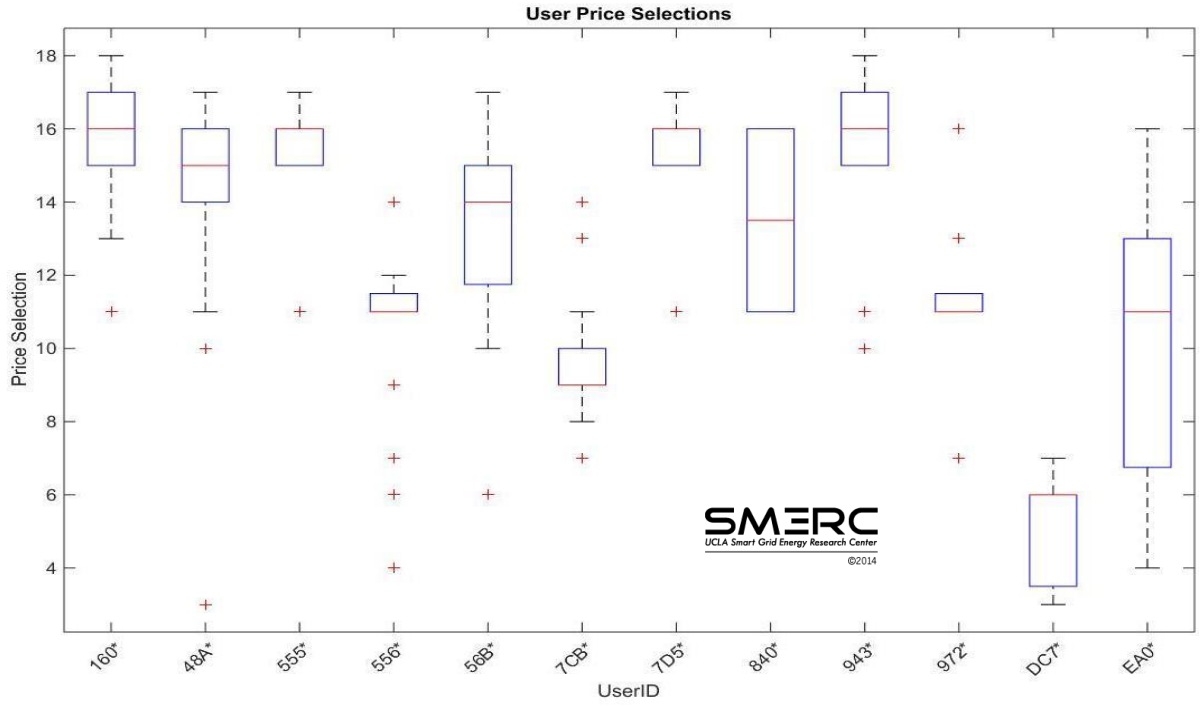


Figure 14: Box-Chart for User Price Selection

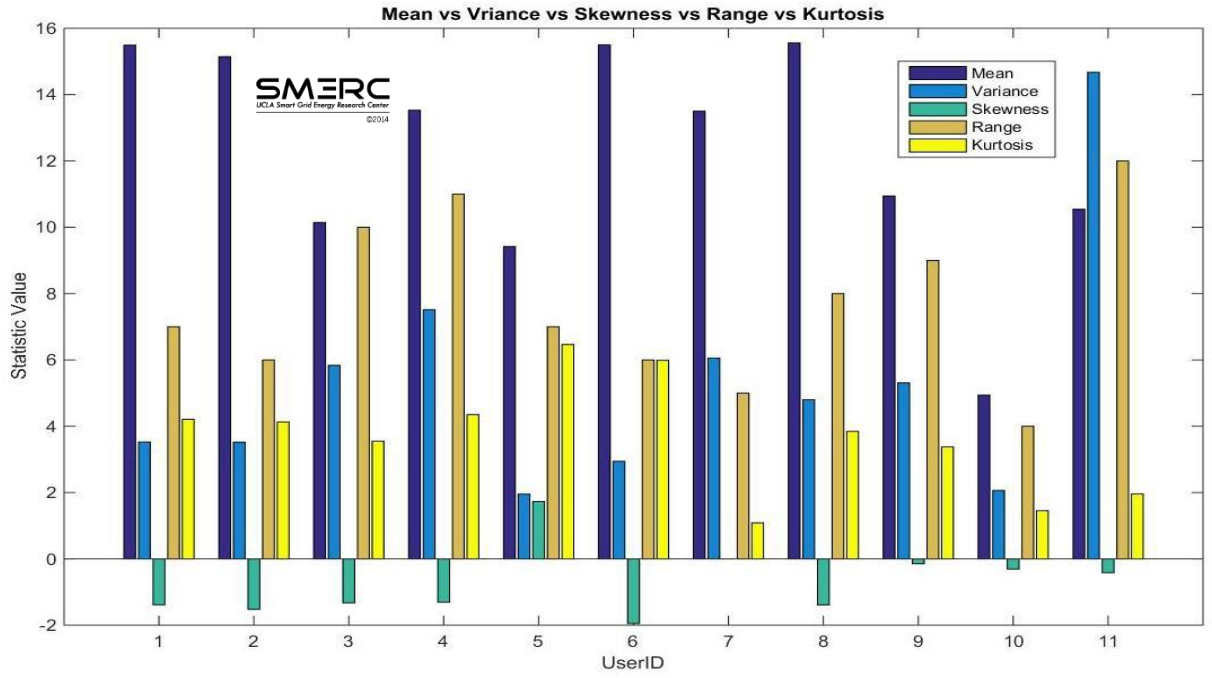


Figure 15: Statistics for Price Selections

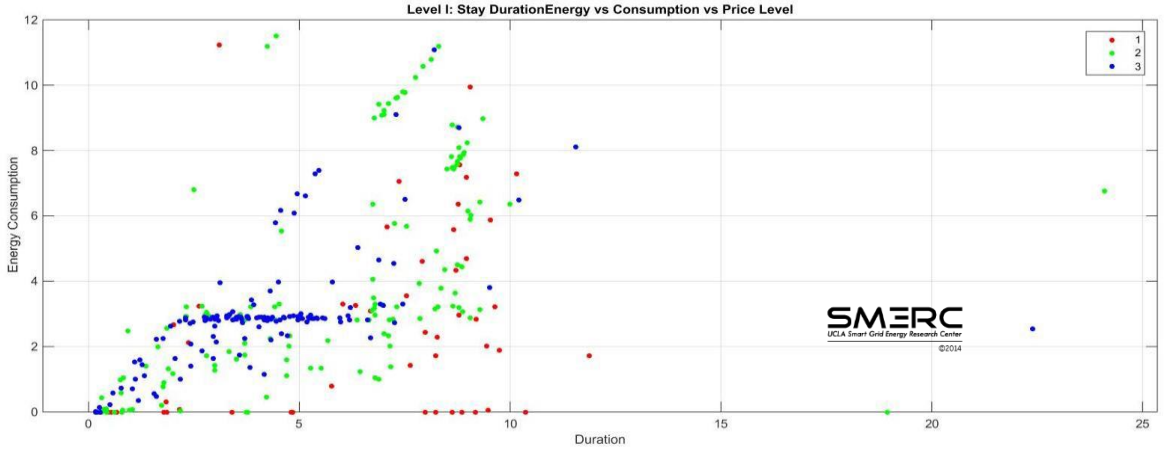


Figure 16: Impact of Price Selection on Charging Schedules

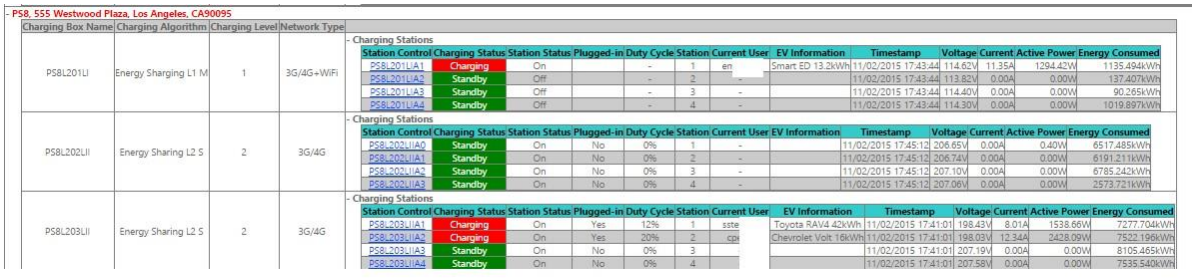


Figure 17: Priority Charging Sessions



Figure 18: Station Records for Priority Charging

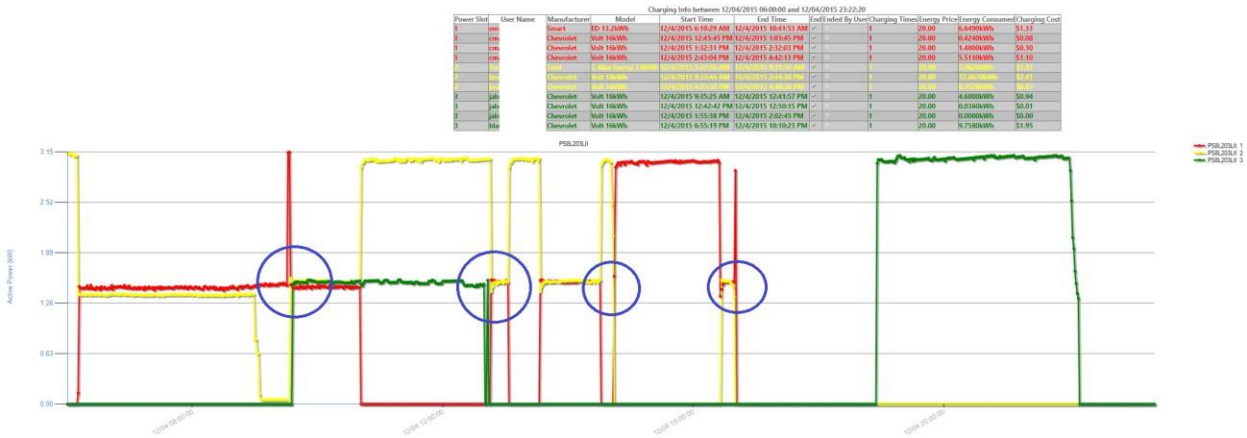


Figure 19: Unstable Priority Charging

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Appendix AE UCLA TPR Use Case 6

Technology Performance Report (TPR)
Use Case (Demonstration) #6
June 25, 2016

Demo/Use Case Name: Use of Batteries in the Grid (G2V Only)

Brief Description:

The purpose of this use case was to demonstrate aggregation of electrical loads between chargers for Grid-to-Vehicle (G2V) charging only. These included level 1, 2, & 3 chargers.

Design Document Methodology (anticipated in 2011)

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. By utilizing the EV chargers installed at UCLA, the UCLA EV team gathered charging data at all of the parking structures at UCLA and found load profiles regarding the electrical loads from charging EVs.

Demo responsibilities

Charging aggregated EVs could result in the overloading of transformers at the distribution level. While charging, each EV could consume between 2-10 times more power of a single electric home. Charge rates varied depending on levels of charging. Considering the public adoption of Level 2 charging, which required 220V and more than 50A of current, the amount of power that a single EV could possibly consume was very high. The challenge with EV integration was to balance the load of a large number of charging EVs by working with the vehicles' onboard BMS to handle charging, given that charging current varies nonlinearly with time and percent of charge.

Consumer behavior must also be factored when estimating power consumption in an EV aggregate scenario. Because EV loads during peak periods had strong potential to overload the system, optimization of charging schedules limited severe loading issues. Identifying active charging stations and monitoring State of Charge (SOC) allowed for greater flexibility of charging schedules. The SG EV Control Center factored various criteria to determine charging levels to ensure both safety and stability of the grid.

Demo steps and flow

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. EV Vitals & Scenario Data sent to Control Center
4. Control Center sends commands to Charging Station
5. Charging Station charges EV per commands

6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data
7. EV informs Station charging is complete
8. Charging Station reports results of charge to Control Center
9. Charging Station inform operator results of charging session
10. EV Operator removes & stores Charging Cable
11. Charging Station resets for new charging session

Planned approach

21. Monitor and evaluate data from EV chargers
22. Document and report on the load profiles of EVs

Final Used Methodology

Key changes in Demo design and justification

The original Use Case design was based on obtaining power consumption information from each individual EV charger. With current development on UCLA SMERC's Super Control Center (SCC) technology, the power consumption information could be obtained on parking structural level through interaction with EV control Center with WINSmartEV™ Infrastructure.

Additionally, the challenges of obtaining Status of Charger (SOC) prevented the UCLA EV team from obtaining SOC regularly from connected EVs. Therefore, the Use Case was modified as below:

1. Vehicle operator plug in the vehicle when arrived at the charging station
2. Vehicle operator use mobile application to activate a charging station
3. Control Center records initial Charging Record (starting status)
4. Control Center sends commands to Charging Station to activate the charger
5. Charging Station charges EV with appropriate current based on charging scheduling algorithm
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data
7. Control Center detects very little current are being drawn by the EV
8. Control Center records final Charging Record (ending status)
9. Control Center sends commands to end the charging session
10. Control Center informs vehicle operator results of charging session
11. Control Center resets the Charging Station for new charging session

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- 137 EV Chargers (Level 1, 2, and 3)
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification"**

Progress vs. success criteria

1. Vehicle operator plug in the vehicle when arrived at the charging station - **Complete**
2. Vehicle operator use mobile application to activate a charging station - **Complete**
3. Control Center records initial Charging Record (starting status) - **Complete**
4. Control Center sends commands to Charging Station to activate the charger - **Complete**
5. Charging Station charges EV with appropriate current based on charging scheduling algorithm - **Complete**
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging station data - **Complete**
7. Control Center detects very little current are being drawn by the EV - **Complete**
8. Control Center records final Charging Record (ending status) - **Complete**
9. Control Center sends commands to end the charging session - **Complete**
10. Control Center informs vehicle operator results of charging session - **Complete**
11. Control Center resets the Charging Station for new charging session - **Complete**

Observations and Results

Observations and Results

Based on the modified use case design, the focus of this use case was to collect aggregated EV power consumption and to observe the EV charging Load peak demand for the purpose of potential demand response program. The UCLA EV team was able to accomplish this Use Case by utilizing Super Control Center's data aggregation approach to interact with EV Control Center in UCLA WINSmartEV™ Infrastructure.

Based on Weekly EV Charging Load profile, the UCLA EV team concluded that most of the workplace charging had the majority of the EV charging load during weekday and almost no EV charging load during weekend. This conformed to the expectation.

Based on Daily EV Charging Load profile, the UCLA EV team concluded that most of the people started their charging session at around 8 am and completed their charging in the early afternoon around 2-3 pm.

The DC Fast Charger (Level 3 Charger) in Parking Structure 4 at UCLA was the dominant EV Charging load among all EV Charging stations on Campus.

Lessons Learned

None established.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected numerous data points from 137 Level 1, Level 2, and Level 3 EV chargers for 5 months. These data points include the timestamp and the total active power of all stations in each parking structure at UCLA.

Data Collection Summary

Location	Voltage	Connector type	Plug Points	Max Power (kW)
PS 9 Level 4	120 V	NEMA 5-15	4	1.8
PS 9 Level 6	120 V	NEMA 5-15	4	1.8
PS 8 level 2 South	208 V	J1772	4	6.6
PS 8 level 2 North	208 V	J1772	4	6.6
PS 2 level 2	120 V	NEMA 5-15	4	1.8
PS 3 level 4	120 V	NEMA 5-15	4	1.8
PS 3 level 2	208V	J1772	4	6.6
PS 4 Box 1	208 V	J1772	4	6.6
PS 4 Box 2	208 V	J1772	4	4.2
PS 2	208 V	J1772	4	6.6
DCFC PS 4	480 V	CHAdeMO	1	50
Total			41	94.4

Table 1: Participating Charging Station

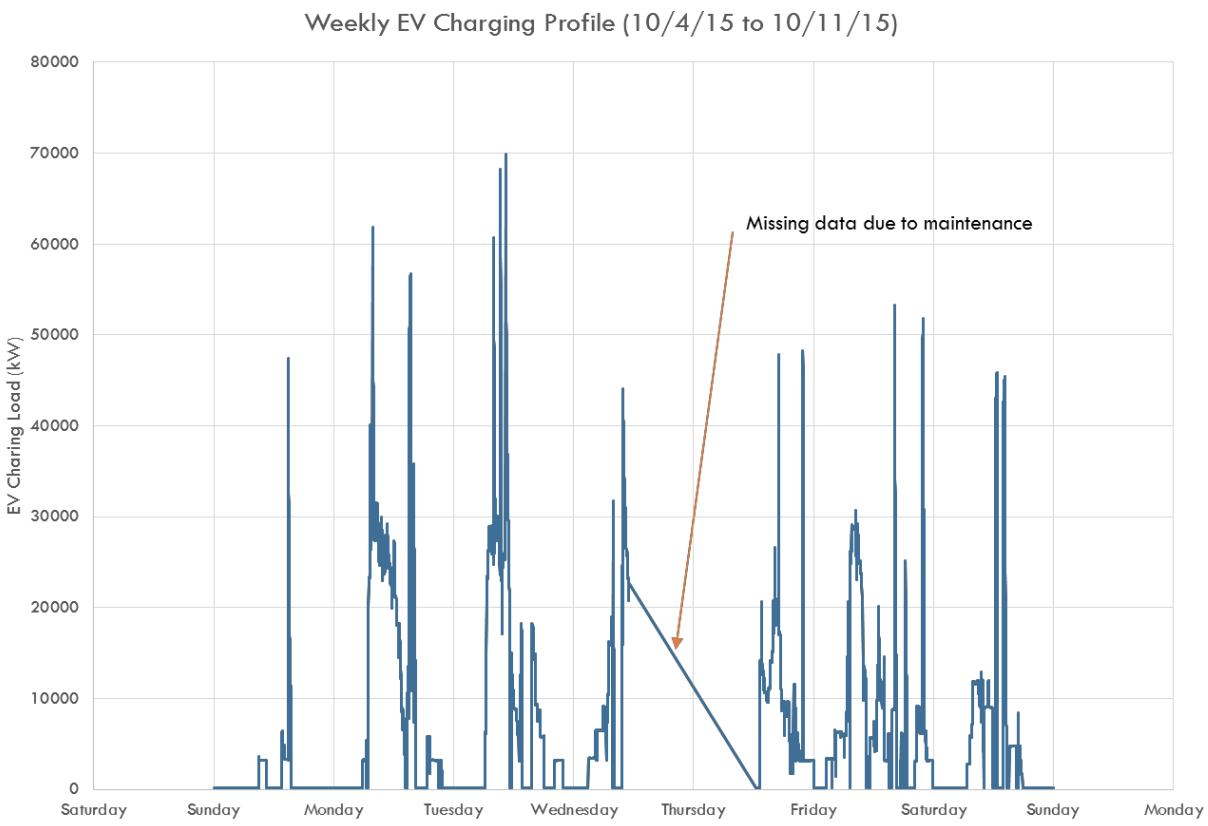


Figure 1: Weekly EV Charging Profile Week of Oct 4 2015

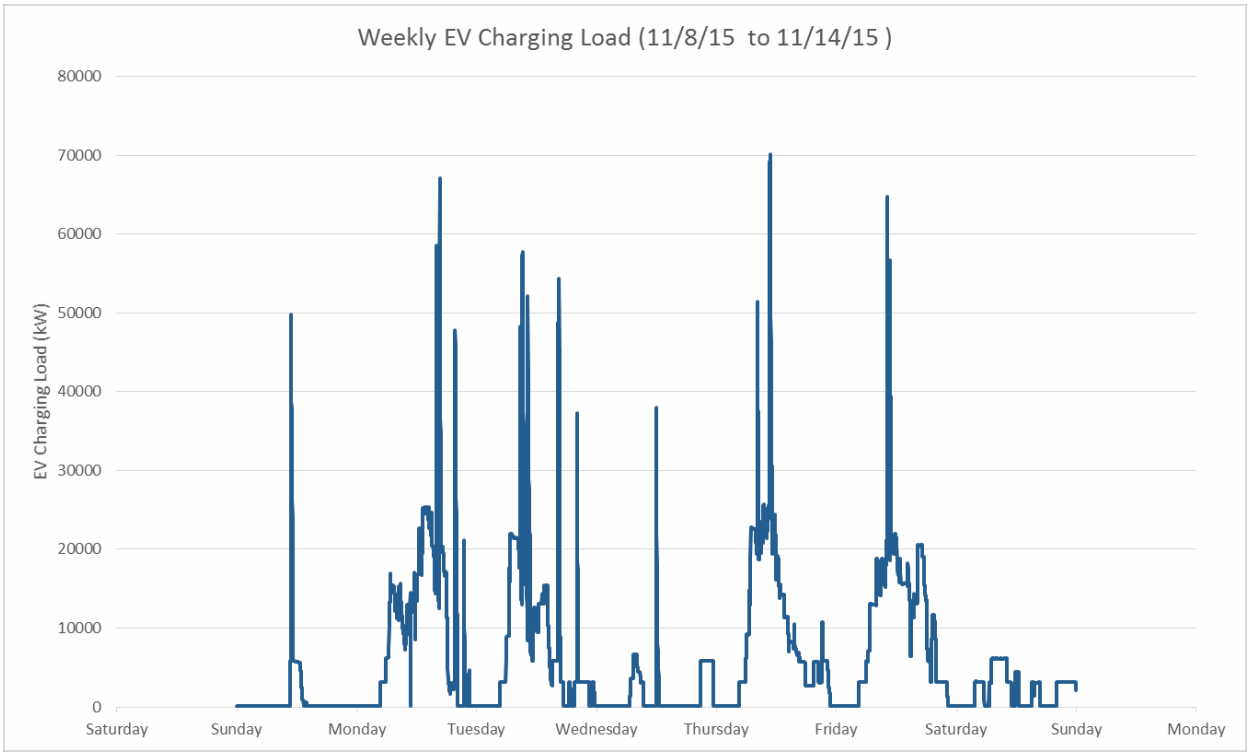


Figure 2: Weekly EV Charging Profile Week of Nov 8 2015

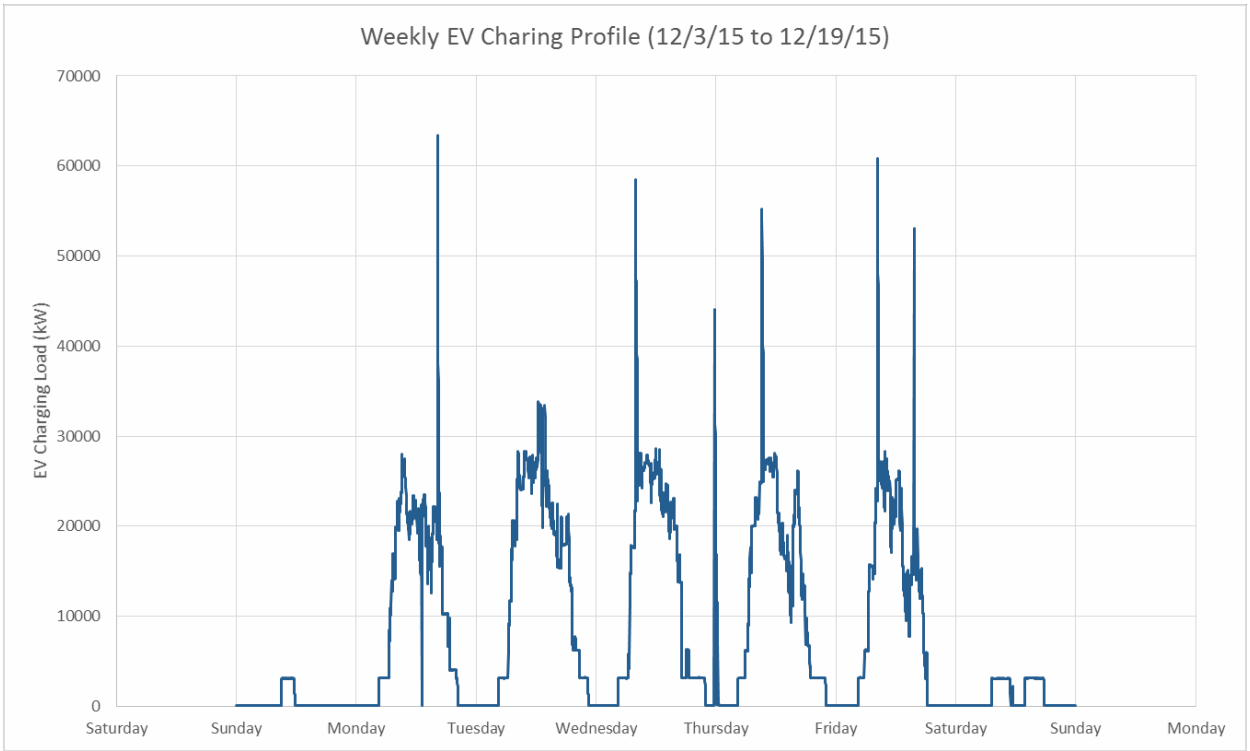


Figure 3: Weekly EV Charging Profile Week of Dec 3 2015

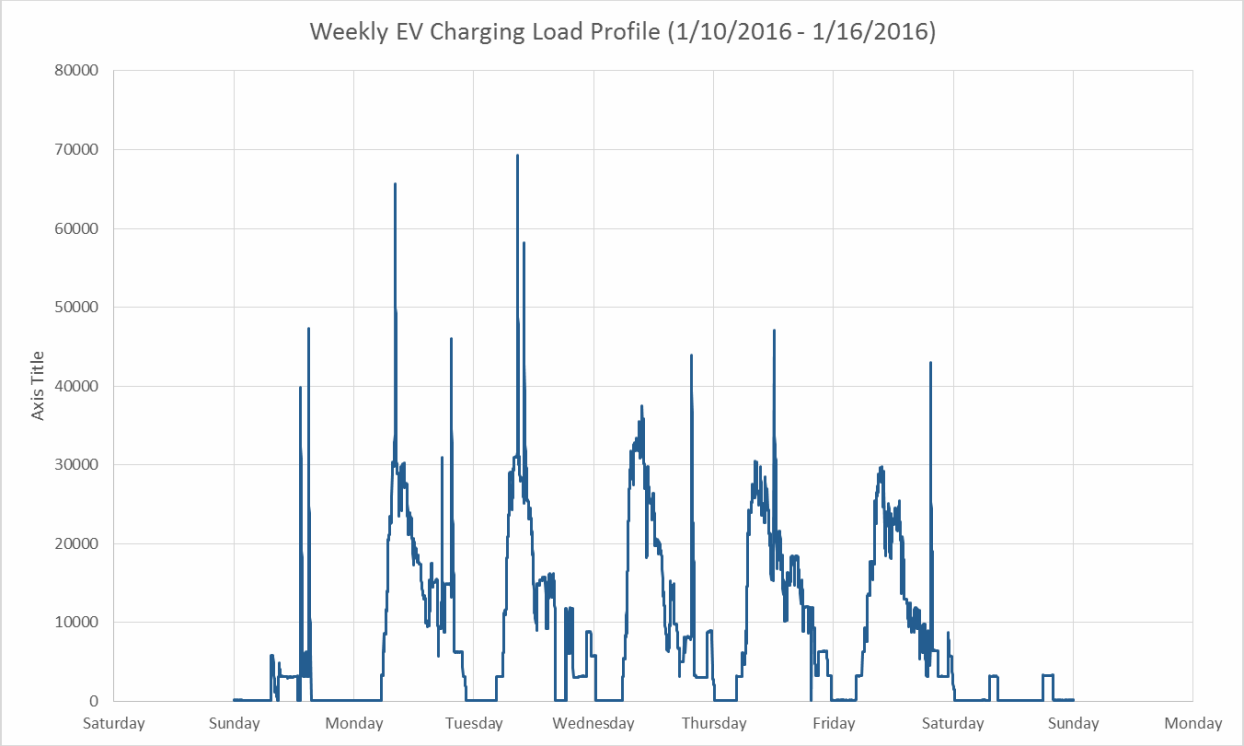


Figure 4: Weekly EV Charging Profile Week of Jan 10 2016

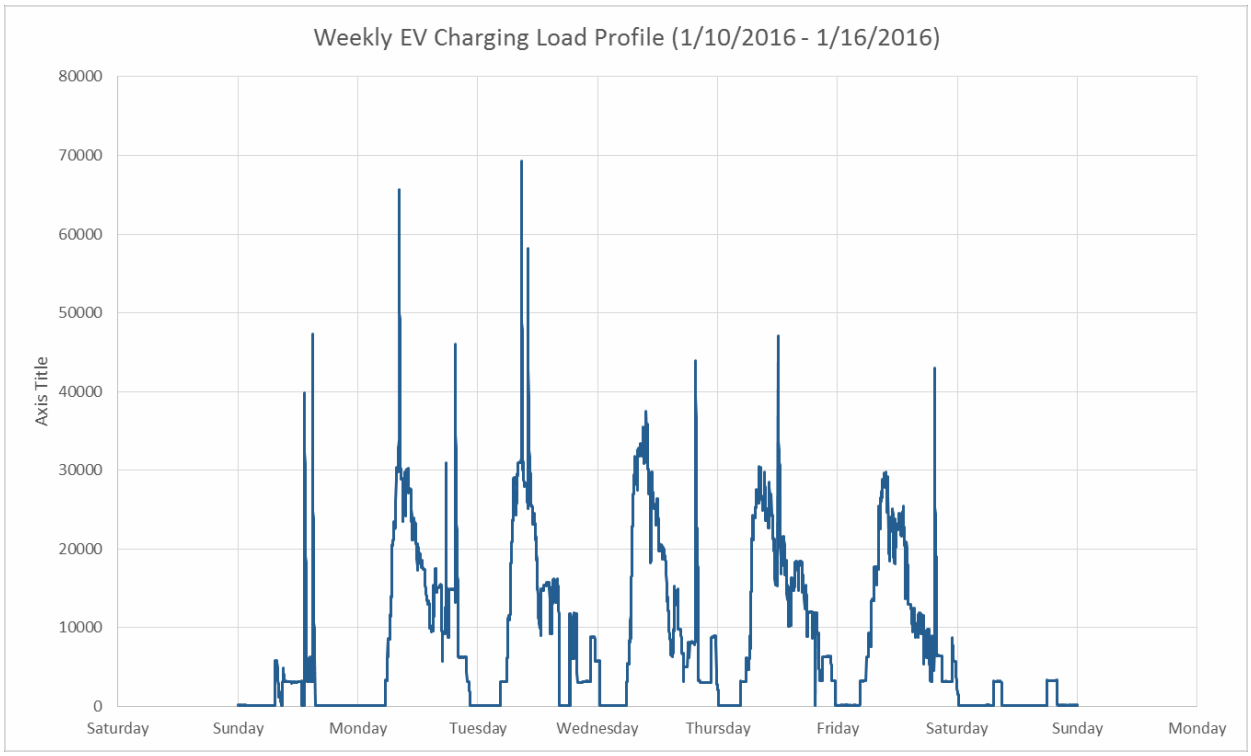


Figure 5: Weekly EV Charging Profile Week of Feb 21 2016

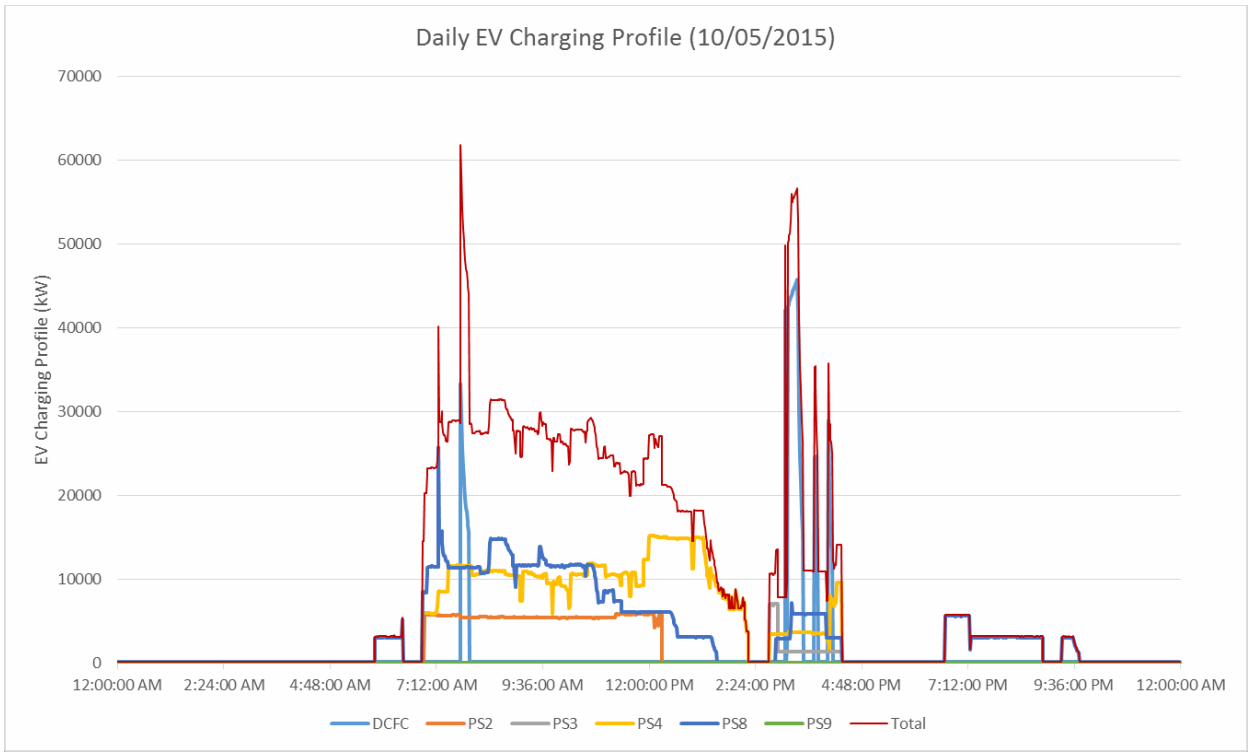


Figure 6: Daily EV Charging Profile (Oct 5 2015)

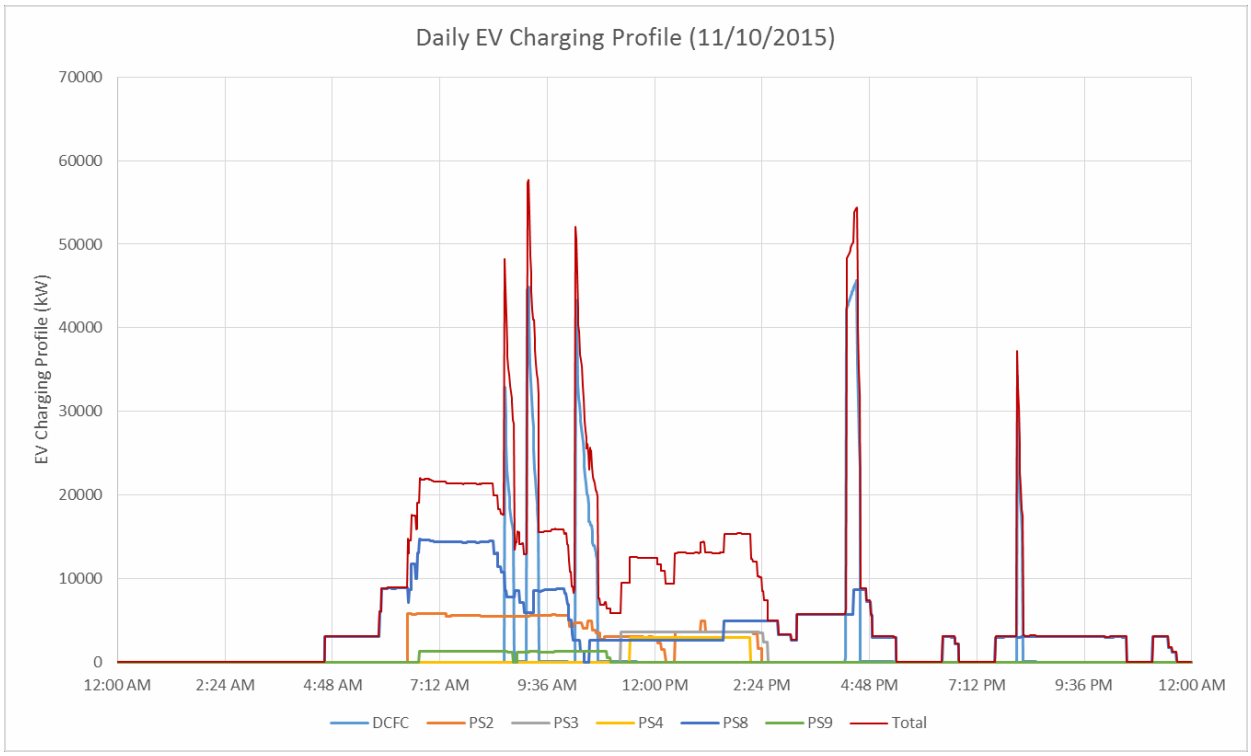


Figure 7: Daily EV Charging Profile (Nov 10 2015)

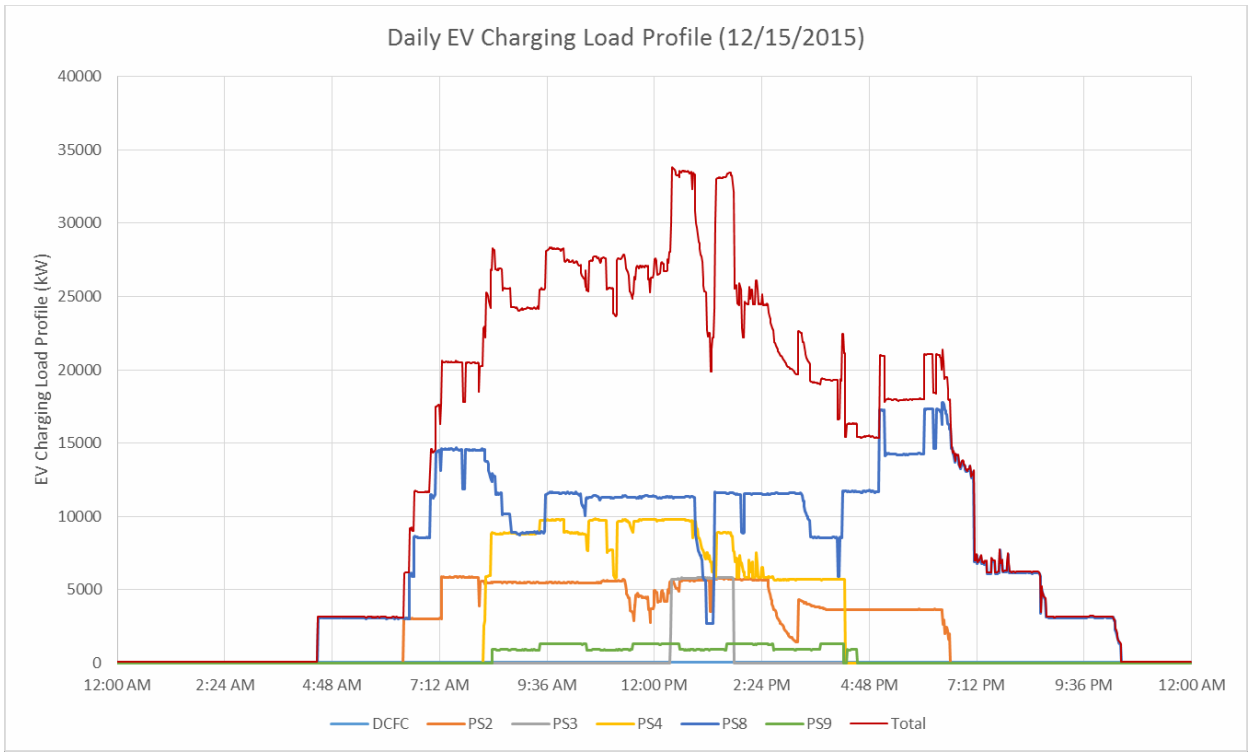


Figure 8: Daily EV Charging Load Profile (Dec 15 2015)

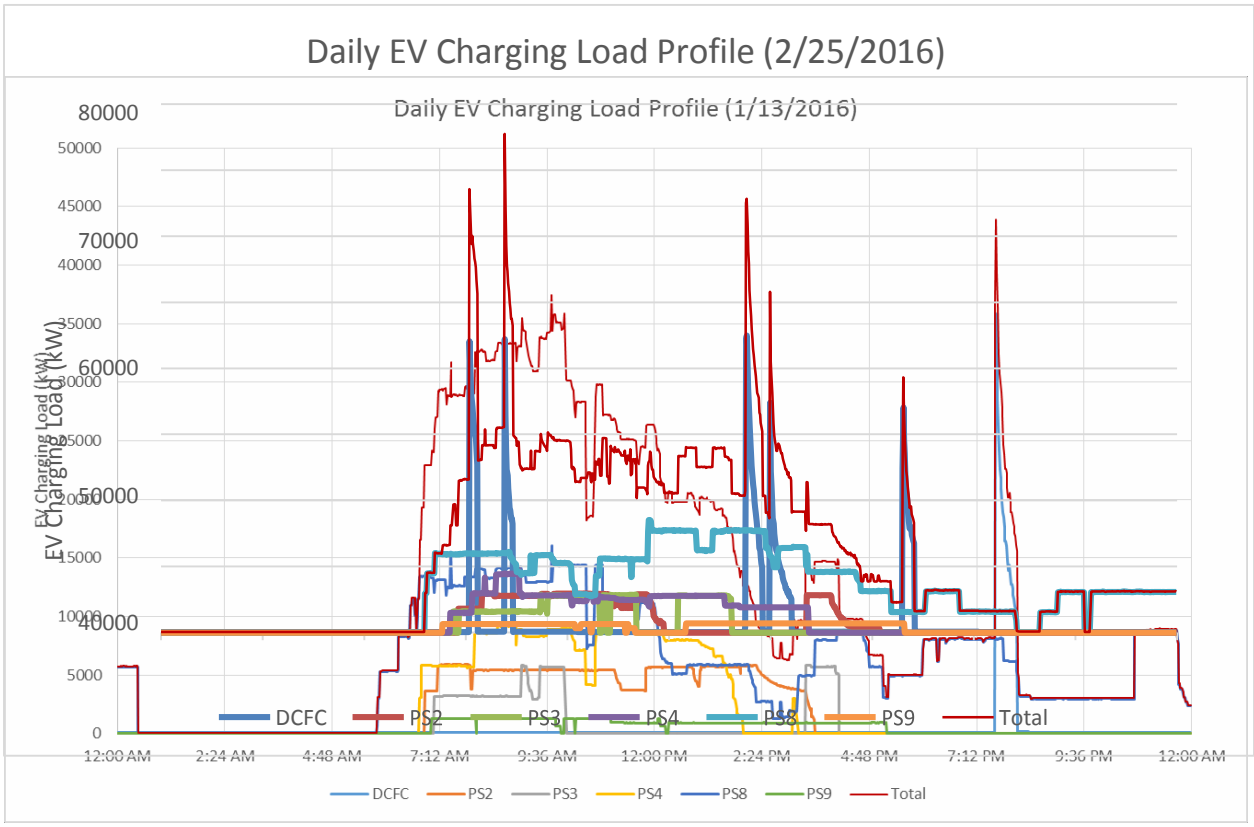


Figure 9: Daily EV Charging Load Profile (Jan 13 2016)

Figure 10: Daily EV Charging Load Profile (Feb 25 2016)

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Appendix AF UCLA TPR Use Case 7

Technology Performance Report (TPR)
Use Case (Demonstration) #7
June 25, 2016

Demo/Use Case Name: Use of Batteries in Grid – V2G (2-way charging)

Brief Description:

The purpose of this use case was to utilize Vehicle-to-Grid (V2G) technology and to charge and discharge multiple vehicles at the same time into the grid. Based on the time-of-use price variation in a day, decisions were formed at the Control Center and a corresponding signal was sent and received by a V2G local controller to determine EV charging and discharging operations.

Design Document Methodology

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. Additionally, the team developed the Mitsubishi i-MiEV Power Box. The Power Box was created because EVs did not have V2G capabilities and an external device was needed in order to provide them with these capabilities.

Demo responsibilities

The EV Project team installed appropriate grid-tie inverters and bi-directional AMI Smart meters at certain charging stations to demonstrate Vehicle-to-Grid (V2G) and G2V operations. Depending on the make and model of the EV, battery backfill might not be possible without modifying the BMS and other circuits on the EV. The EV Project team studied and investigated a non-destructive approach to implement this demonstration. All EVs that were participating in the V2G demonstration may need to be equipped with additional circuits and modules.

Introducing backfill of EV charge, or V2G discharge, had the potential to introduce new issues for the both EVs and the power system. Considering that existing EVs might not have a Battery Management System for the reversal of charge flow, precautions were taken to monitor and control the rate of discharge from EVs to ensure maximum battery lifetime. This demonstration took into consideration the power source/sink management optimization. Taking into account a range of variables, such as time of day and battery status of charge, optimization algorithms were developed to charge vehicles according to consumer scheduling, utility grid management, and battery safety. The control system enabled the EV Project team to simulate, test, and implement optimization control of EV charging/discharging.

Simulations were performed in a controlled environment in order to implement the algorithms to ensure safety and quality control. Once simulation is complete, implementation of

the optimization control were performed on actual EVs. During the times where energy was flowing back into the electrical grid, data was collected in 15- minute intervals to ensure the EV battery did not sustain any damage due to discharging.

Demo steps and flow

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. Charging Station records session parameters collected from EV operator
4. EV Vitals, Scenario Data, & session parameters sent to Control Center
5. Control Center process all data received
6. Control Center sends commands to Charging Station to charge & discharge EV batteries per session parameters
7. Charging Station charges/discharges EV per commands received
8. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data
9. EV informs Station charging is complete
10. Charging Station reports results of charge to Control Center
11. Charging Station inform operator results of charging session
12. EV Operator removes & stores Charging Cable
13. Charging Station resets for new charging session

Planned approach

23. Research and develop V2G equipment
24. Monitor and evaluate data from the Mitsubishi i-MiEV
25. Document and report on V2G technology

Final Used Methodology

Key changes in Demo design and justification

Due to the lack of V2G technology, the UCLA EV team was required to retrofit a vehicle to in order to complete this use case. Because of this, the demonstration flow was modified to the following:

1. Charging Station records Scenario Data
2. Charging Station records Session Parameters collected from EV operator
3. Scenario Data, & Session Parameters sent to Control Center
4. V2G Control Center process all data received
5. V2G Control Center sends commands to Charging Station to charge & discharge EV batteries per Session Parameters automatically
6. Charging Station charges/discharges EV per commands received
7. On a periodic basis, Charging Station will report to V2G Control Center status and accumulative charging data
8. EV operator stop charging/discharging operation
9. Charging Station reports results of charge/discharging to V2G Control Center
10. EV Operator removes & stores Charging Cable and V2G equipment
11. Charging Station resets for new charging session

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- Mitsubishi i-MiEV grid tied inverter (discharge interface)
- Mitsubishi i-MiEV

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification"**

Progress vs. success criteria

1. Charging Station records Scenario Data - **Complete**
2. Charging Station records Session Parameters collected from EV operator - **Complete**
3. Scenario Data, & Session Parameters sent to Control Center - **Complete**
4. V2G Control Center process all data received - **Complete**
5. V2G Control Center sends commands to Charging Station to charge & discharge EV batteries per Session Parameters automatically - **Complete**
6. Charging Station charges/discharges EV per commands received - **Complete**
7. On a periodic basis, Charging Station will report to V2G Control Center status and accumulative charging data - **Complete**
8. EV operator stop charging/discharging operation - **Complete**
9. Charging Station reports results of charge/discharging to V2G Control Center - **Complete**
10. EV Operator removes & stores Charging Cable and V2G equipment - **Complete**
11. Charging Station resets for new charging session - **Complete**

Observations and Results

Observations and Results

This use case focused on a prototyped G2V & V2G system that allowed Mitsubishi i-MiEV to back feed its battery power into the power grid through CHAdeMO port as well as receiving charge through J-1772 port on the vehicle. To control the current of back feed process. Another pair of AC/DC Converter and DC/AC inverter was added into this system.

In this use case, two flows of operation were defined and implemented. The normal operation focused on automated control of vehicle charging/discharging status based on time-of-use price variation. Given energy price throughout a day, with scheduled leaving time and price limit input given by user, the control center would make a decision on charging/discharging schedules and send out control signal automatically. Also, based on the price ahead, an

estimation of energy consumption and cost would also be presented at the very first so EV owners knew how much energy and cost they were going to get when the charging section was finished. Through analysis, the UCLA EV team could see that, although such estimation was not exactly the same as the actual value due to system delay and EV charging/discharging change of status delay, it still had a high accuracy that could be seen as a good indicator and provided ample information for users.

The alternative operation focused on manual control of EV's charging status. This manual function was necessary in the sense that it might be required by certain users/customers. The manual operation allowed users to choose whether they wanted EV to be charging or discharging. Also, under V2G mode, current could be controlled by user. Also, the existence of manual operation would be a backup for the automatic operation. When errors occur in automatic operation, G2V/V2G could be turned off manually.

For V2G operation, it was tested that the best current level would be 5 A to keep the system stable. As current goes up to 8 ~ 9 A, it was more likely to trip off the system due to the vehicle protection scheme, which was not solvable in this case due to inaccessibility of vehicle SOC.

Lessons Learned

The main deficiency in the implementation was the efficiency issue introduced by multiple layers of power electronic device introduced in the process. Though the UCLA EV team was using the industry standard solution in power electronic, the total energy loss after each layer was noticeable. This problem originated from the CHAdeMO protocol. As it was a proprietary protocol, the team could not directly use an inverter to get power from the EV. A Mitsubishi Power Box was used but because it was not grid tied, it resulted in the additional layers of power electronics.

In the future, three main focuses would be pursued. The first focus would be the acquisition of the EV SOC. This would be critical for monitoring and control purposes and for optimization of charging/discharging sequence. With the SOC information, the UCLA EV team could determine the charging/discharging priority base not only on user input but also on actual need. However, it was highly unlikely for the team to get direct information of SOC without the help of EV manufacturers.

Second, besides CHAdeMO, the SAE combo also preserved the capability of V2G operation. It was obvious that a unified protocol would not present itself in the field of V2G and therefore a solution that was regardless to protocol needed to be considered. The goal would be to develop protocol-regardless interface that would allow V2G of different vehicles with different charging ports.

Another focus was the scaling of V2G experiment. The scale up of the system was in two-fold: to scale up feedback power on one EV, and to study multiple EV with V2G capability. The first scale up was necessary in the sense that V2G applications, including peak load shedding and ancillary services, oftentimes required a large energy output. The second scale up was more complicated in the sense that an optimization of charging/discharging sequence concerning user's priority and energy coordination had to be included. Hopefully, through such scale up a

more practical situation could be generated and corresponding solution would provide better guidance to future EV integration to the smart grid.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected numerous data points from the Power Box and the EV charger for 5 months. These data points include the timestamp, voltage, current, power, energy, power factor, apparent power, frequency, instantaneous price of energy, the accumulative cost of energy, sell limit, estimated cost, estimated energy, and leave time.

Data Collection Summary

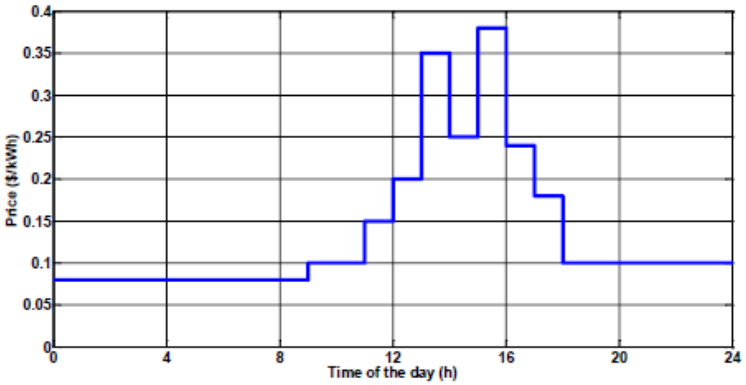


Figure 1: Day-Ahead Price of a Day

V2G

SETTINGS and RECORDS

Item	Interface	Operation
Leave time	HH 16 MM 0	Change
Sell Limit	$ 0.26	Change
V2G Current	5	SUBMIT
History Settings	Pick Day Show Hours	SHOW
Command	REFRESH Stop	
Cost	$ -0.0011400000000000433	
Energy	-0.0030000000000001137 kWh	
Expected Cost	$ -0.0014583333333333796	
Expected Energy	0.3141666666666666 kWh	

Figure 2: User Interface for Estimation on Energy and Cost of a Day

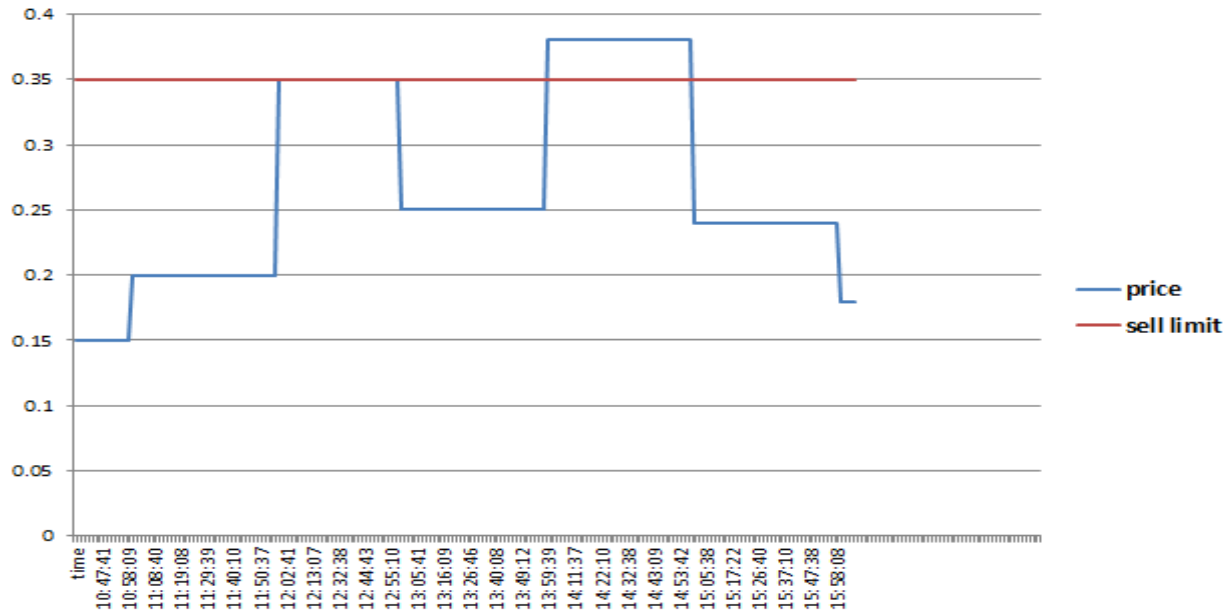


Figure 3: Price and Sell Limit of a Day

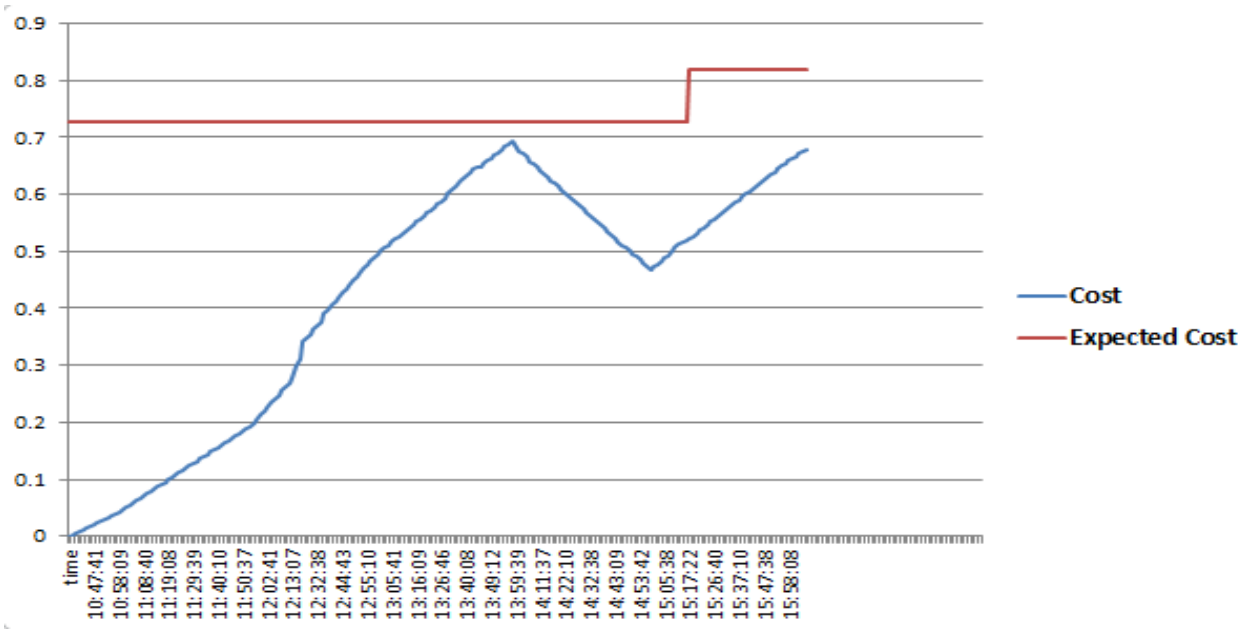


Figure 4: Cost and Expected Cost of a Day

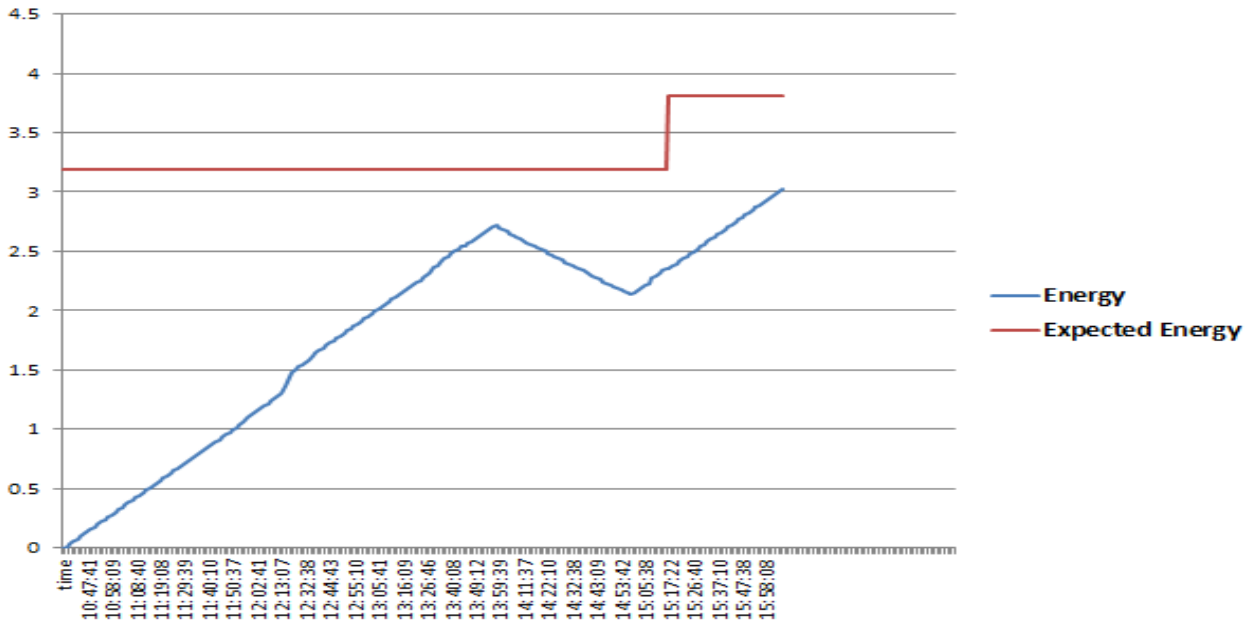


Figure 5: Energy Consumption and Expected Energy Consumption of a Day

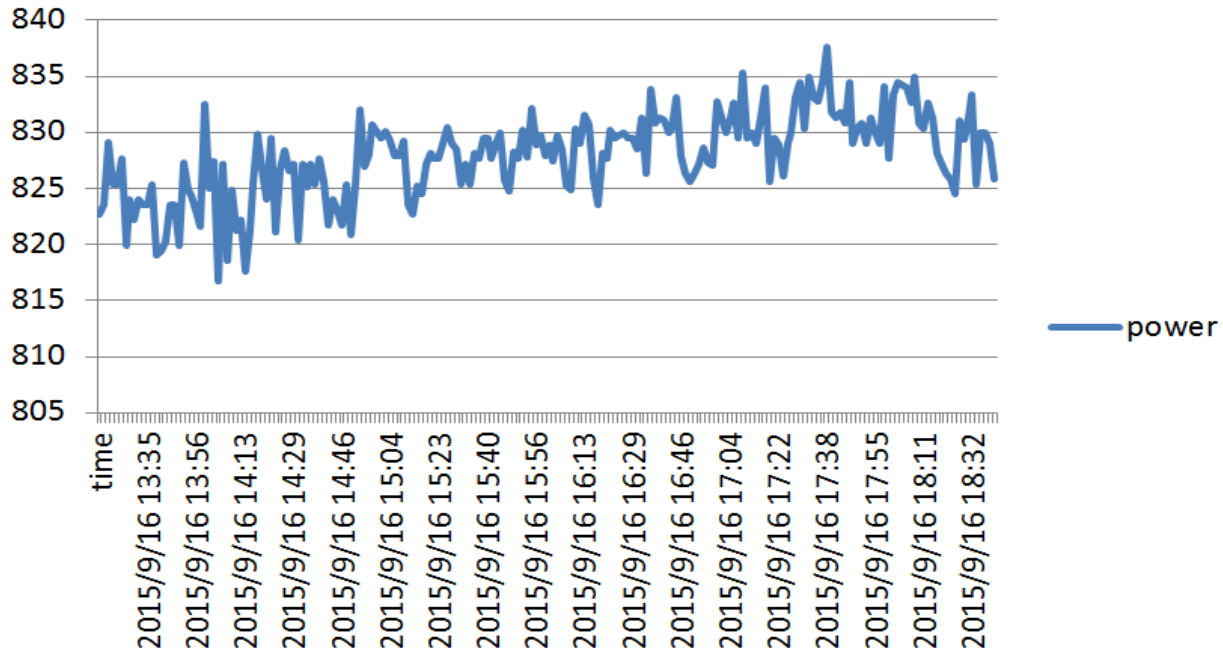


Figure 6: Collected Power Data of a Day

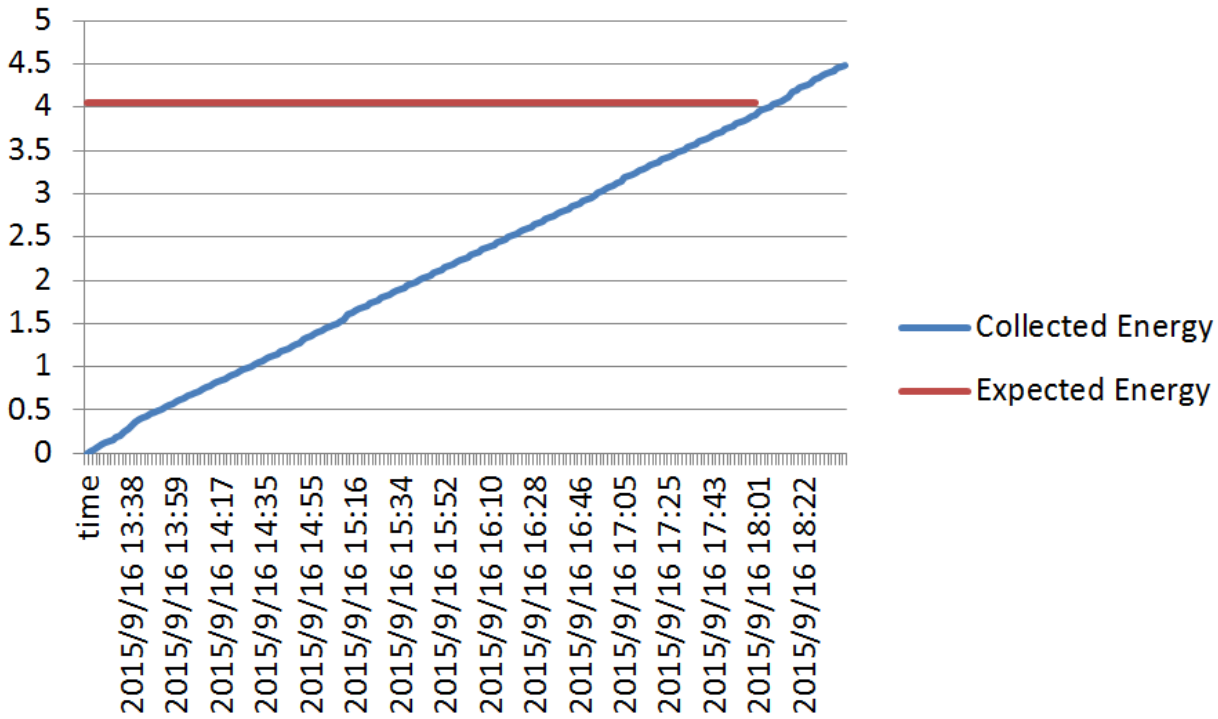


Figure 7: Comparisons of Expected Energy And Collected Energy



Figure 8: Transient State from Charging to Discharging

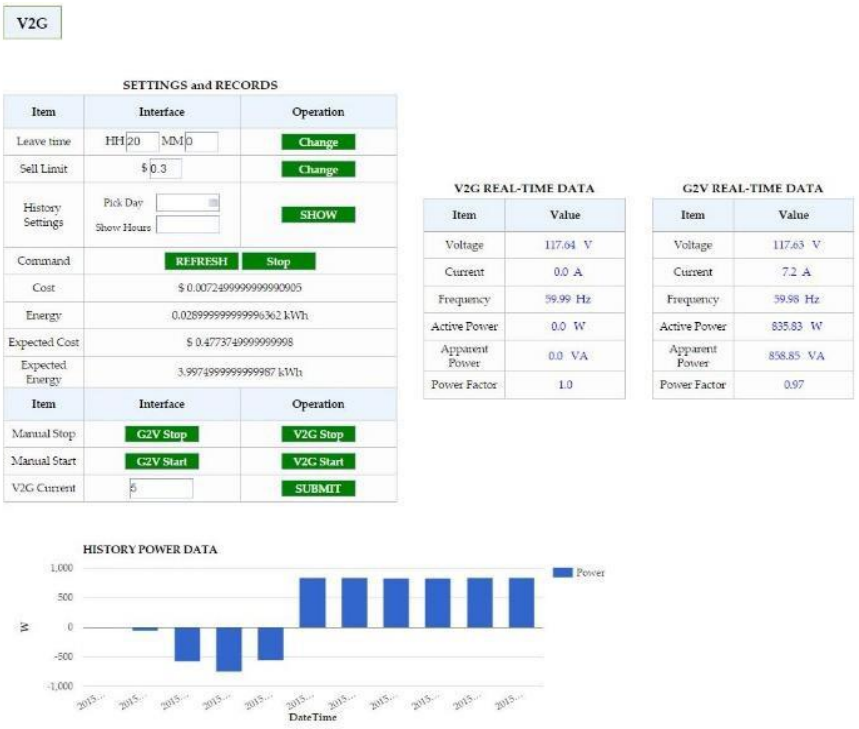


Figure 9: Transient State from Discharging to Charging

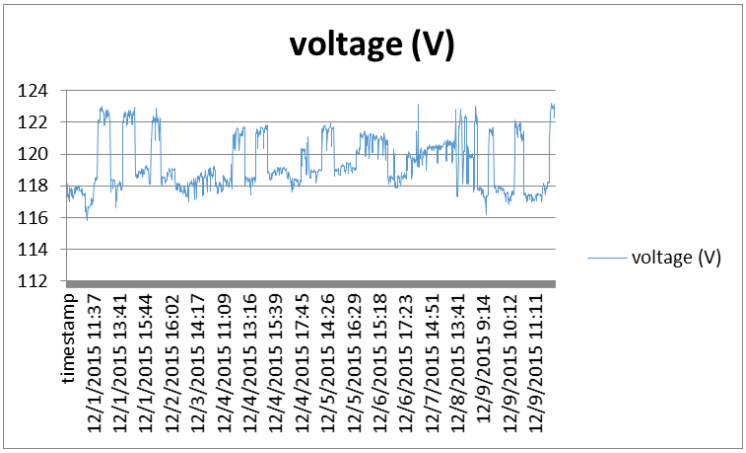


Figure 10: Voltage Data Collected in December 2015

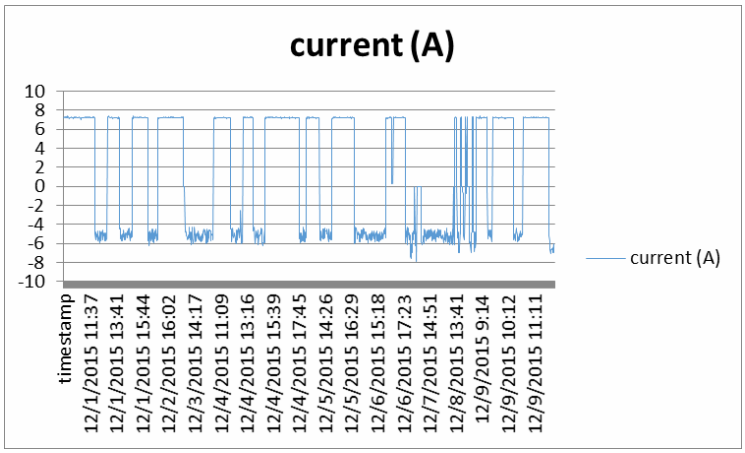


Figure 11: Current Data Collected in December 2015

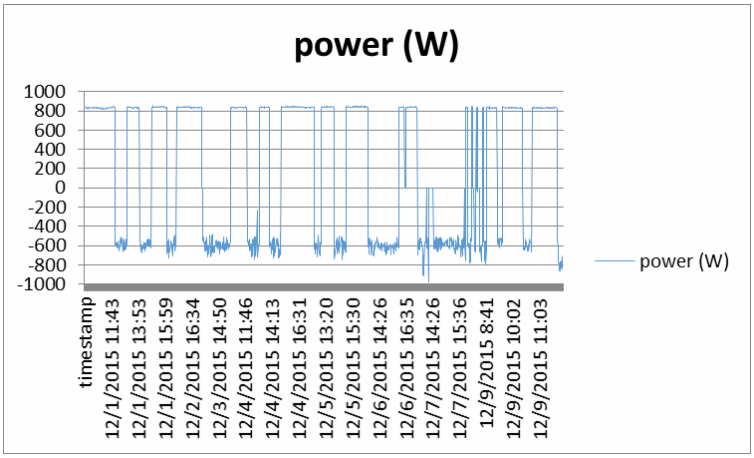


Figure 12: Power Data Collected in December 2015

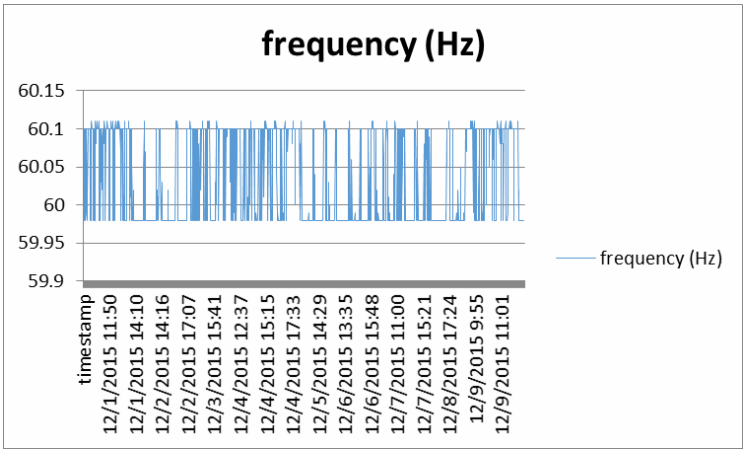


Figure 13: Frequency Data Collected in December 2015

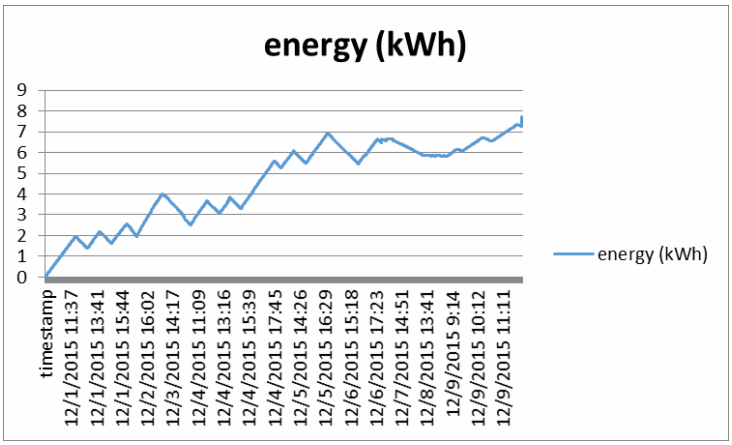


Figure 14: Energy Data Collected in December 2015

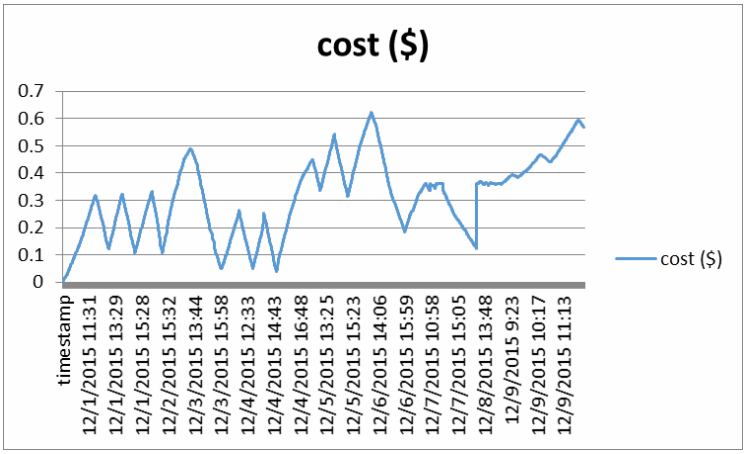


Figure 15: Cost Data Collected in December 2015

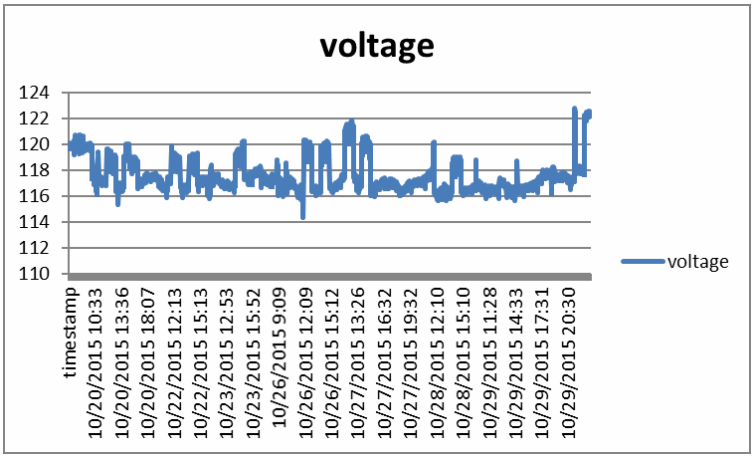


Figure 16: Voltage Data Collected in October 2015

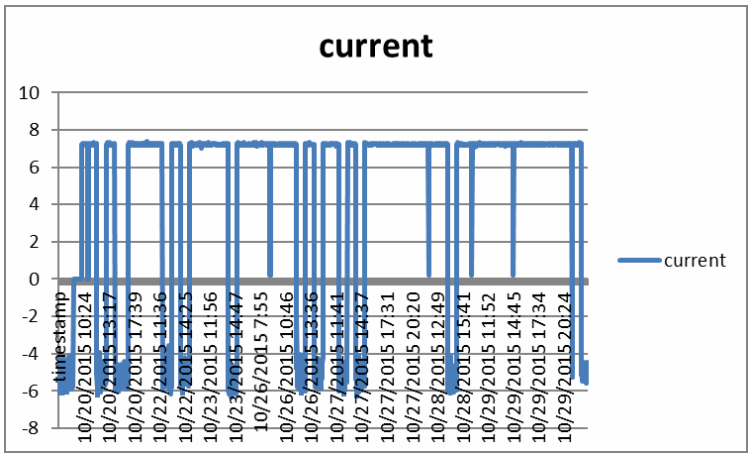


Figure 17: Current Data Collected in October 2015

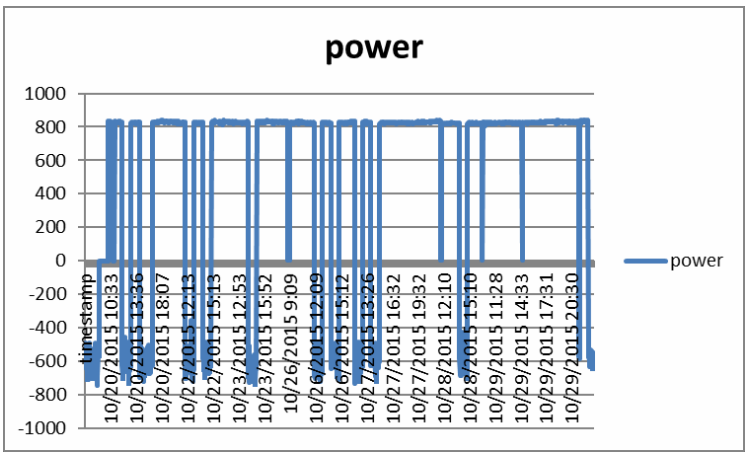


Figure 18: Power Data Collected in October 2015

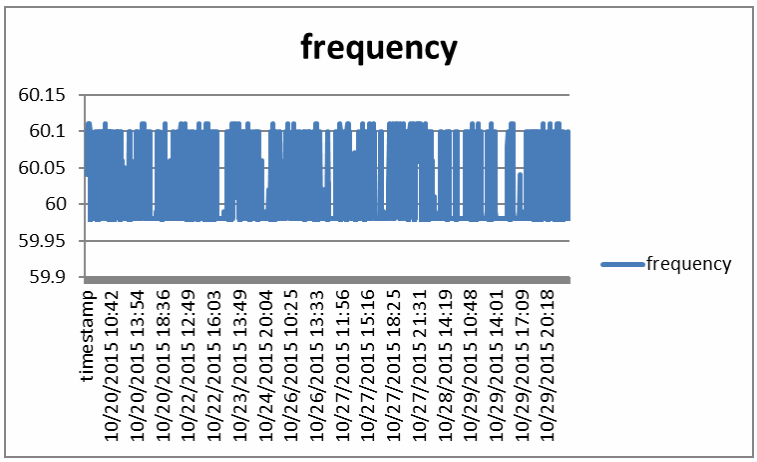


Figure 19: Frequency Data Collected in October 2015

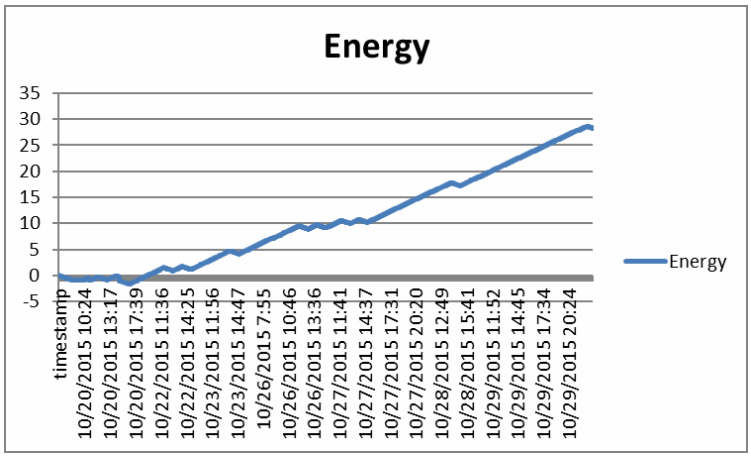


Figure 20: Energy Data Collected in October 2015

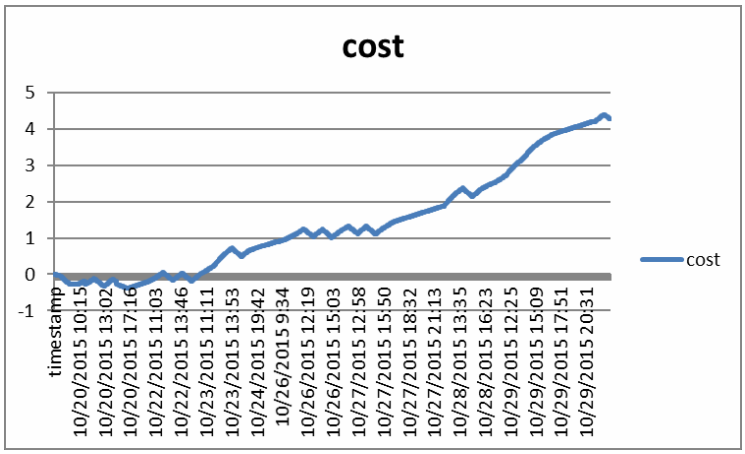


Figure 21: Cost Data Collected in October 2015

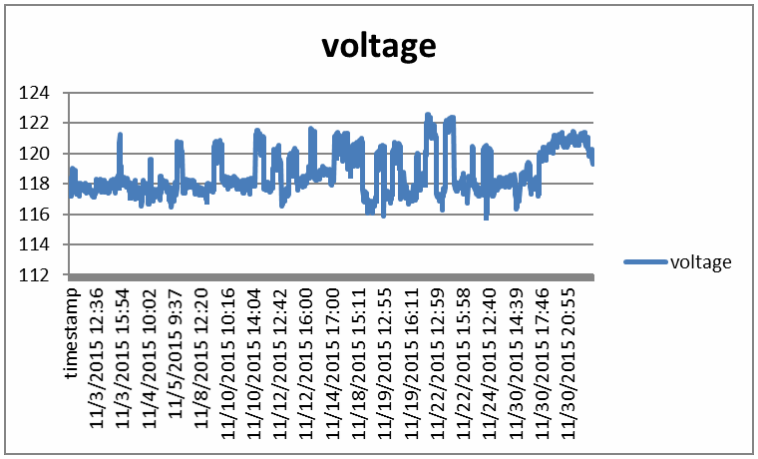


Figure 22: Voltage Data Collected in November 2015

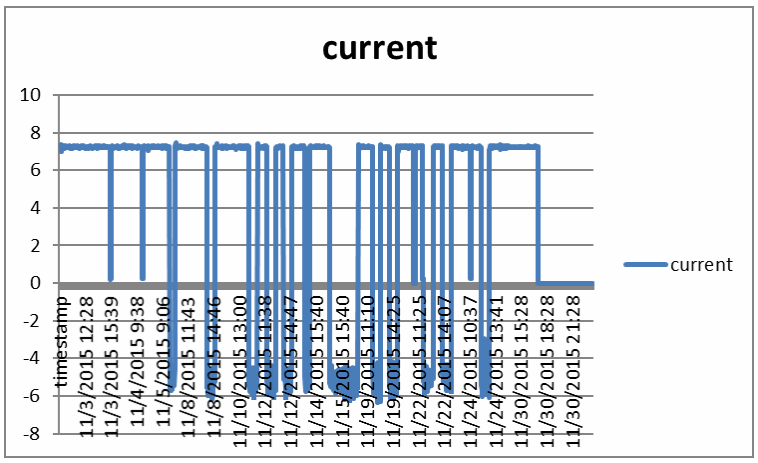


Figure 23: Current Data Collected in November 2015

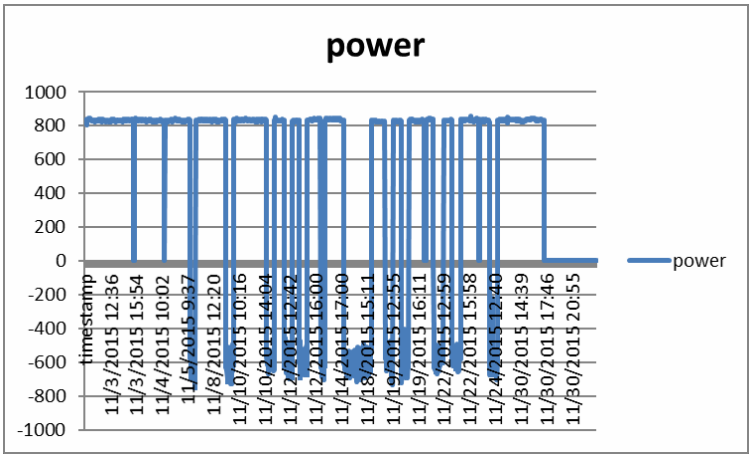


Figure 24: Power Data Collected in November 2015

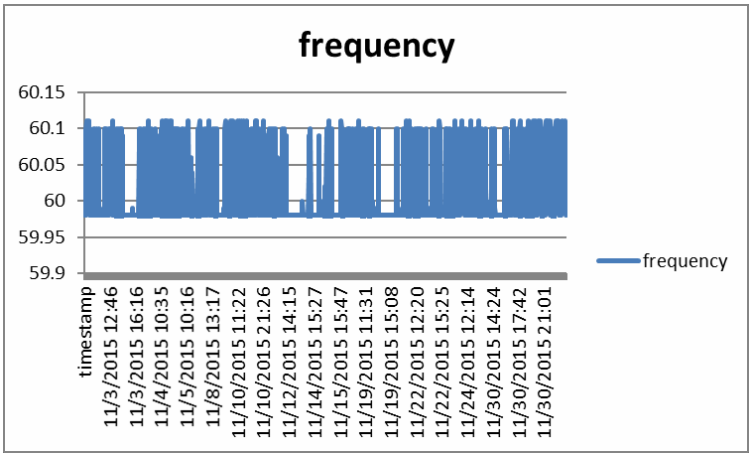


Figure 25: Frequency Data Collected in November 2015

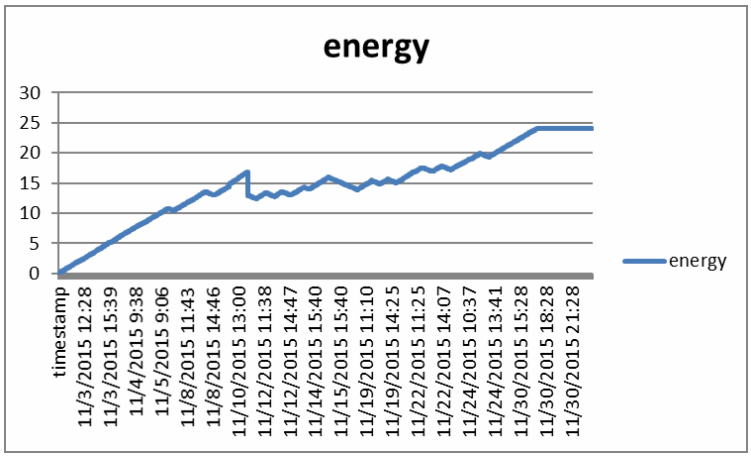


Figure 26: Energy Data Collected in November 2015

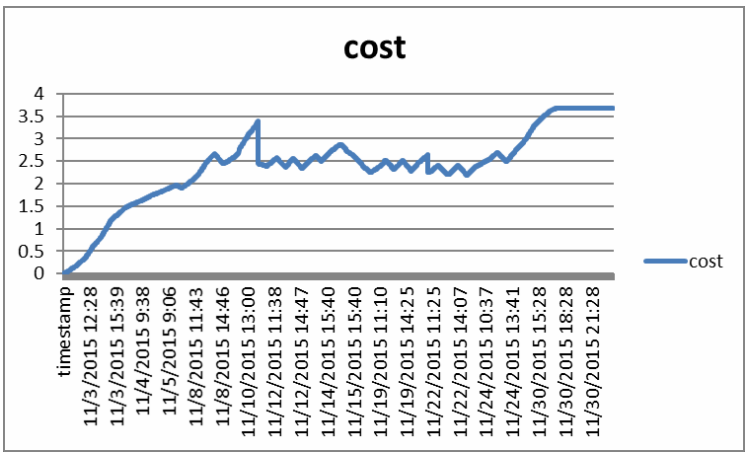


Figure 27: Cost Data Collected in November 2015

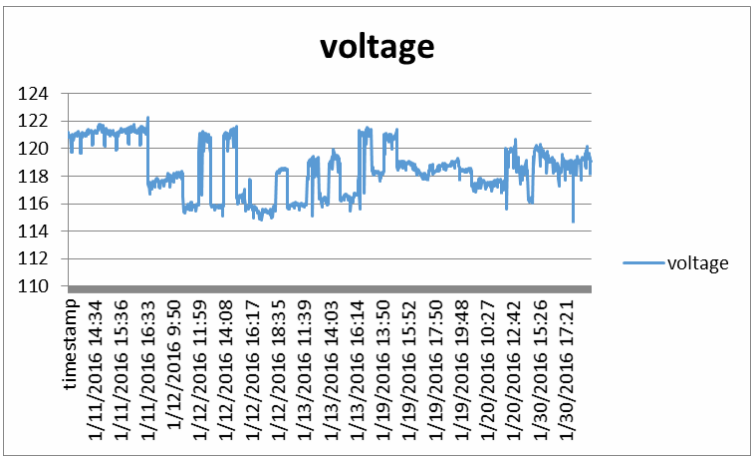


Figure 28: Voltage Data Collected in January 2016

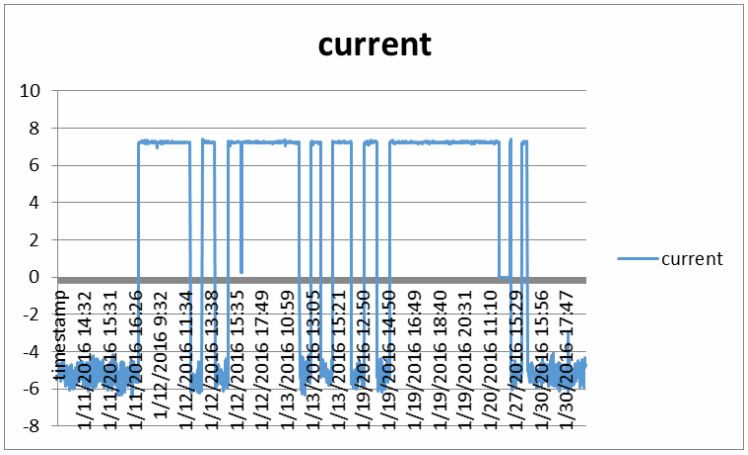


Figure 29: Current Data Collected in January 2016

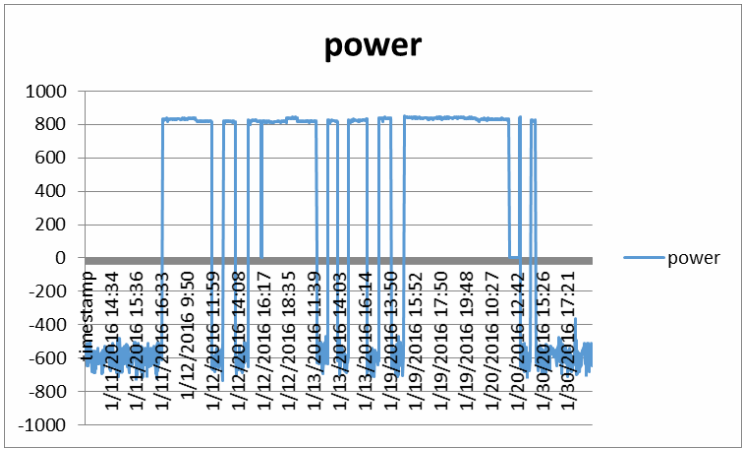


Figure 30: Power Data Collected in January 2016

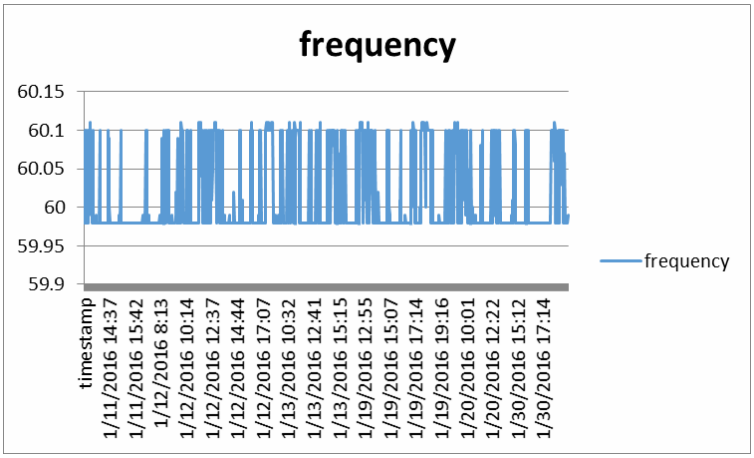


Figure 31: Frequency Data Collected in January 2016

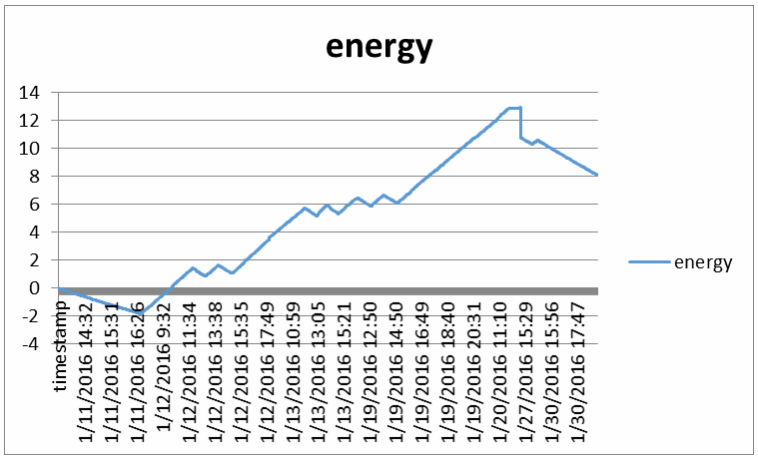


Figure 32: Energy Data Collected in January 2016

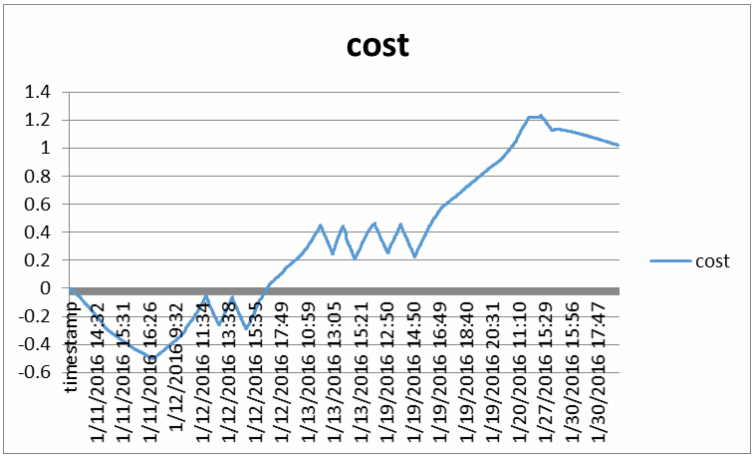


Figure 33: Cost Data Collected in January 2016

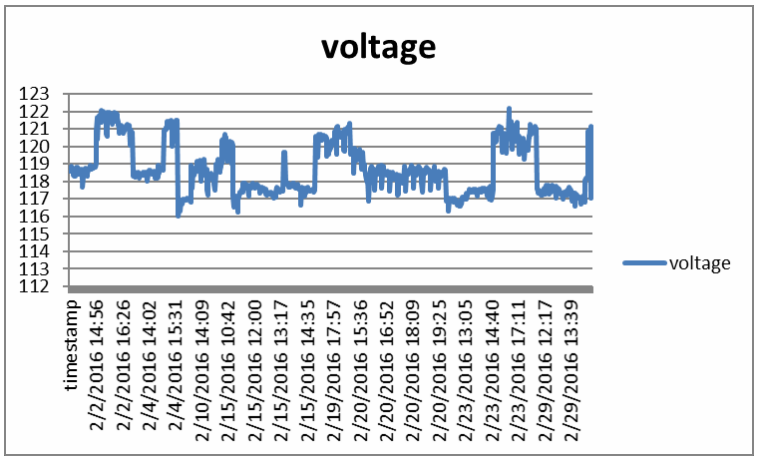


Figure 34: Voltage Data Collected in February 2016

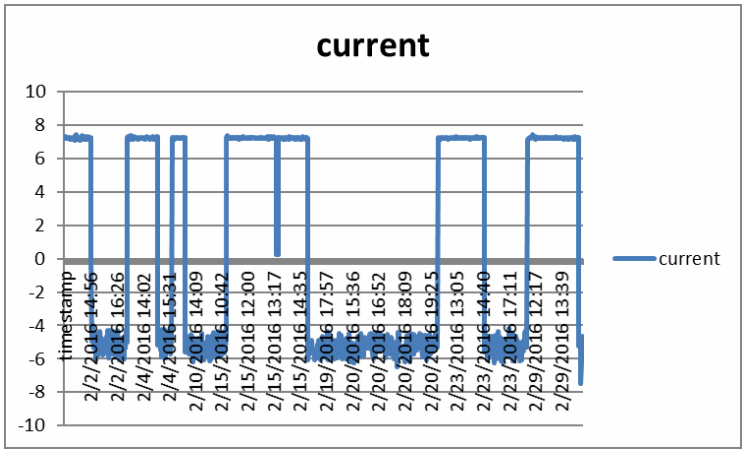


Figure 35: Current Data Collected in February 2016

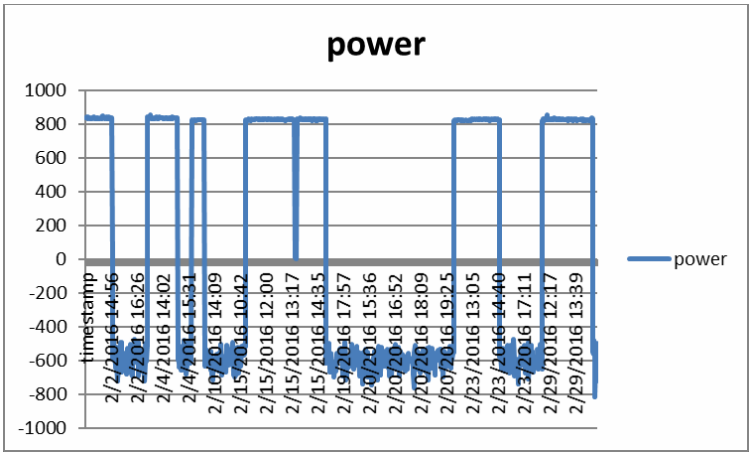


Figure 36: Power Data Collected in February 2016

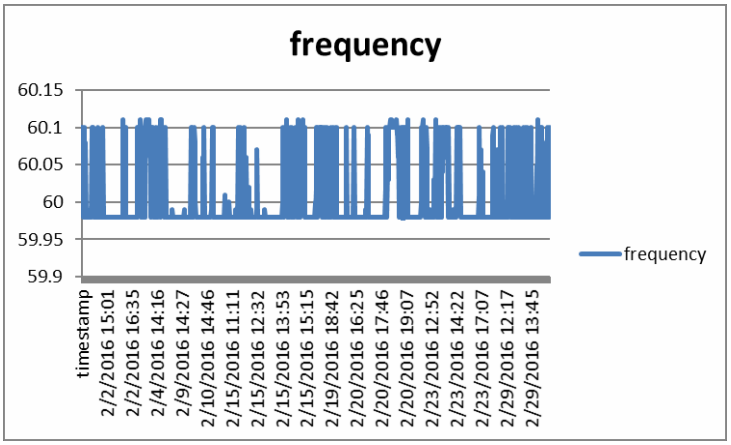


Figure 37: Frequency Data Collected in February 2016

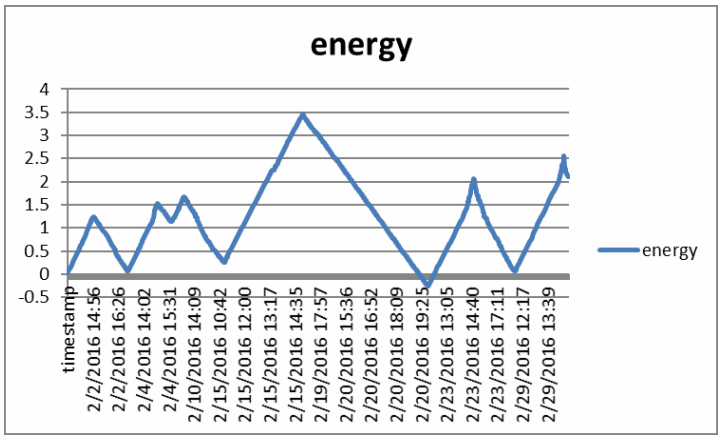


Figure 38: Energy Data Collected in February 2016

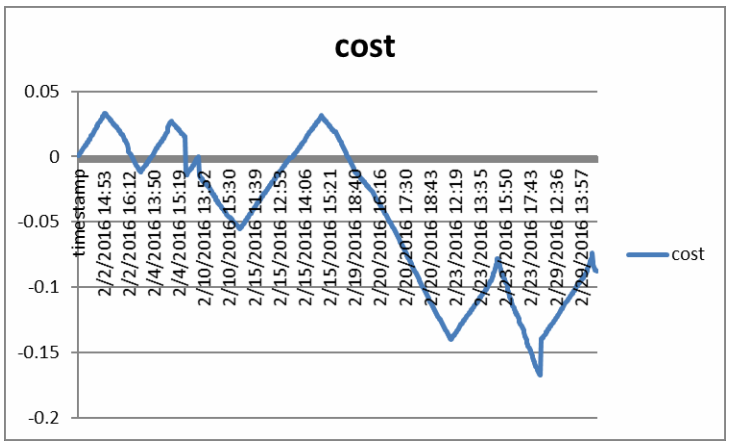


Figure 39: Cost Data Collected in February 2016

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

- By utilizing the V2G technology, utilities and customers will be able to save costs by utilizing EVs to help reduce peak demand. Utilities will save in generation whereas customers will save in demand charges.

Realized Impacts and Benefits to Date

None established. V2G technology is not commercially available to the public.

Appendix AG UCLA TPR Use Case 10

Technology Performance Report (TPR)
Use Case (Demonstration) #10
June 25, 2016

Demo/Use Case Name: Various Vehicles Charging

Brief Description:

The purpose of this use case was to compare the different EV makes and models observed in this project. The vehicles purchased or leased were used to conduct research and perform tests with the design and development of the open architecture EV chargers as described in the design document.

Design Document Methodology

Assumptions

The UCLA EV team utilized the WINSmartEV infrastructure for this use case. Additionally, the UCLA EV team purchased and leased 5 Electric Vehicles, the Nissan Leaf, Chevy Volt, Ford Focus, Mitsubishi MiEV, and the Tesla Model S. The team collected data from each of these vehicles. Additionally, the UCLA EV team collected data from EV Chargers charging various EVs throughout the UCLA campus.

Demo responsibilities

This demonstration performed the tasks on all make and models of EV that were available to the team. The UCLA EV team analyzed a comparison of the performance of various battery types and sizes and their impact on the power grid. The following tasks were completed during this demonstration:

- Monitoring all chargers
- Reading the power consumption for vehicle that are connected to chargers
- Control of chargers
- Use of battery in the grid (G2V)
- Renewable and battery integration

This demonstration was completed at the SG Power Lab, the Various Demo Sites, and the SG EV Control Center. The main participants of the demonstration were LADWP and USC.

Demo steps and flow

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. EV Vitals & Scenario Data sent to Control Center

4. Control Center sends commands to Charging Station
5. Charging Station charges EV per commands
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data
7. EV informs Station charging is complete
8. Charging Station reports results of charge to Control Center
9. Charging Station inform operator results of charging session
10. EV Operator removes & stores Charging Cable
11. Charging Station resets for new charging session

Planned approach

26. Monitor and evaluate data from different EVs
27. Document and report on differences in EVs

Final Used Methodology

This Use Case's design was similar to that of Use Case EV.3, Control of Chargers, where EV control center recorded EV charging sessions and power consumption. Because of this, UCLA SMERC EV Team recommended the following medication:

- Use collected data to conduct analysis in terms of various EV make and Models' power consumption.
- Report J1772 communication issues with various vehicle
- Report energy efficiency and other observations based on the operation of grant vehicles.

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- 137 EV Chargers
- Various Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification**"

Progress vs. success criteria

1. Charging Station records EV Vitals - **Complete**
2. Charging Station records Scenario Data - **Complete**
3. EV Vitals & Scenario Data sent to Control Center - **Complete**
4. Control Center sends commands to Charging Station - **Complete**
5. Charging Station charges EV per commands - **Complete**

6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data - **Complete**
7. EV informs Station charging is complete - **Complete**
8. Charging Station reports results of charge to Control Center - **Complete**
9. Charging Station inform operator results of charging session - **Complete**
10. EV Operator removes & stores Charging Cable - **Complete**
11. Charging Station resets for new charging session - **Complete**

Observations and Results

Observations and Results

Some of the specific observations the UCLA EV team found included the following: impacts on voltage drop on the ability to send power to the vehicle and that in certain vehicles, such as the Chevy Volt, the sensitivity-to-voltage fluctuations on the ability to get a charge was high; the inability to re-start a stopped charging session after the charging cable was disconnected on the Ford Focus; and the contrast with the flexibility of input characteristics such as the above on the consistency of the charging behavior of Nissan Leaf. The UCLA EV team continuously conducted experiments such as the above and included these results in the final deliverable reports. Such variations in behavior were also resulting in us modifying the nature of the architecture of our system so as to make the overall architecture more robust and reliability in the presence of multiple EVs. Additionally, where feasible, the team reached out to the various EV manufacturers about some of our findings and pursued various lines of discussion on potential solutions by way of technological solutions and/or standards modifications so as to standardize the communications between the EVs, the charging stations, and eventually the smart grid.

Drivers with different vehicle makes, different commute distances, different work habits such as where they charge (at home, in the office, in public places, etc.), and different work hours had different requirements for charging preferences. To be able to accommodate such a multitude of influencing factors on the smart charging scheduling, the purchased and leased vehicles were assigned to researchers and staff in the UCLA EV project team with various EV charging needs/preferences to test the scheduling algorithms. The driver also utilized the mobile application developed in this research to specify his/her charging preference based on the make and model of the vehicle that was assigned to him/her. Eventually, the decision of where to charge, when to charge, how much to charge, and which algorithms to be used to charge an EV would depend on a combination of personal driver preferences, facilities available for charging in parking facilities (such as at work, at home and at public places), and the programs offered by the grid operators including TOU pricing, renewable energy availability, etc.

Due to the significant variations in features among the different vehicles, in addition to the above usage for charging an EV, the Mitsubishi MiEV was also used for V2G development and research, the Nissan Leaf was used to level 3 CHAdeMO interface and backfill research, the Chevy Volt was used as a influencing factor for being a hybrid vehicle, and the Tesla Model S was used for design and test of higher charging power experiments. In addition, the Nissan

Leaf and Chevy Volt were also both used to develop status of charge (SOC) modules to transmit battery SOC and Battery Management System (BMS) fault signals to the EV chargers and then back to the control center as an input to smart scheduling.

1. Nissan Leaf

Nissan Leaf was used for smart charging (Level 1, 2 and 3) demonstration. The charger design took into consideration the flexibility of charging behavior of Nissan Leaf. Due to its compatible with the CHAdeMO protocol, it was also used for research in Level 3 chargers. It was also used for research in battery SOC monitoring. SOC modules were designed for the Nissan Leaf to transmit battery SOC and BMS fault signals to the EV chargers and then back to the control center as an input for smart scheduling. Observation and tests were conducted to study Nissan Leaf's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support, and limited time, it was not feasible to perform V2G demonstration on these vehicles at this time.

2. Chevy Volt

The Chevy Volt was primarily used in smart charging (Level 1 and 2) demonstration. Charger design took into consideration the impacts of unable to charge due to voltage drop (below 190 VAC) on the vehicle. On algorithm design end, the Chevy Volt was considered as an influencing factor for being a hybrid vehicle (less urgent charging need than pure electric). SOC modules were designed for the Chevy Volt to transmit battery SOC and BMS fault signals to the EV chargers and then back to the control center as an input for smart scheduling. However, at a recent vehicle software update, the SOC information was further encrypted and the team was unable to retrieve this information.

Another observation of the Chevy Volt was its alarm system that was activated when the EVSE lost power. This problem was resolved by changing the setting inside the vehicle.

Due to the fact that it had only an AC onboard single-direction charger, the Chevy Volt was not used for V2G demonstration. Observation and tests were conducted to study the vehicle's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support, and limited time, it was not feasible to perform V2G demonstration on this vehicle.

3. Ford Focus

The Ford Focus was primarily used in smart charging (Level 1 and 2) demonstration. Charger design took into consideration the fact that it was unable to re-start charging session after charging disconnection of Ford Focus. Another observation was that the Ford Focus did not start charging if the charging session power was not provided within 5 minutes after it was plugged in.

Due to the fact that it had only an AC onboard single-direction charger, the Ford Focus was not used for V2G demonstration. Observation and tests were conducted to study Ford Focus's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support, and limited time, it was not feasible to perform V2G demonstration on these vehicles.

4. Mitsubishi-MiEV

Mitsubishi MiEV was primarily used for demonstration of power back-feeding, smart charging (Level 1, 2, and 3) and design of renewable integration. The Mitsubishi MiEV was equipped with both J1172 and CHAdeMO, making it compatible with three levels of charging. The V2G function developed was based on the V2X box. Currently, the V2X box was used to withdraw the AC 100 V power from the vehicle and then the AC power was converted into 48 V DC and then connected through a grid-tie inverter to conduct V2G project.

5. Fiat 500e

The Fiat 500e model could only charge using the full power source. In addition, the EV user must submit a charging request to make the pilot signal draw a high current before plugging-in the cable. The initialization charging process failed if the duty cycle of the pilot signal was small, which indicates only low charging current was available. If the initial duty cycle was high and later changed to low, the Fiat EV generated error messages of "Service Vehicle Electrical System" and "Service Your Charging Station".

Conclusion

Based on the data collected and user's observation, the Nissan Leaf had the most compatible J1772 pilot signal communication schema. Various challenges were observed and identified throughout the duration of this project. However, the Nissan Leaf's battery also had the most battery degradation rate among the grant vehicles.

In UCLA Campus, the Nissan Leaf and Chevy Volt were two of the most popular vehicles while Tesla Model S 70 kWh had most energy per session.

Lessons Learned

- State of Charge (SOC) information was difficult to obtain because of car manufacturers and because the J1772 standard did not provide SOC information. In most cases, the SOC was entered manually.
- The Tesla vehicle had numerous integration issues.
- Pricing and scheduling algorithms had to be reevaluated in order to compensate for the Tesla integration issues.
- Multiple issues involving individual EVs were documented throughout the demonstration. The UCLA EV team was able to debug the majority of the issues.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected data from July 2014 to February 2016. This data includes the EV type, start time, end time, and energy consumption.

Data Collection Summary

Grant Vehicles	Energy Efficiency (miles/kWh)	Battery size	Average Range when fully charged	Battery degradation and other battery related observations
Tesla Model S	3.81	60 kWh	208	No obvious degradation observed.
Nissan Leaf	4.30	24 kWh	72	Obvious degradation observed, battery depth reduced by about 3-5 % after 2 years of testing
Chevy Volt	3.49	16 kWh	40	The battery condition is still very good.
Ford Focus	3.21	23 kWh	70	Minor degradation observed
Mitsubishi i-MiEV	3.97	16 kWh	61	Used for V2G experiment. Not enough data to make observation.

Table 1: Tested EV List

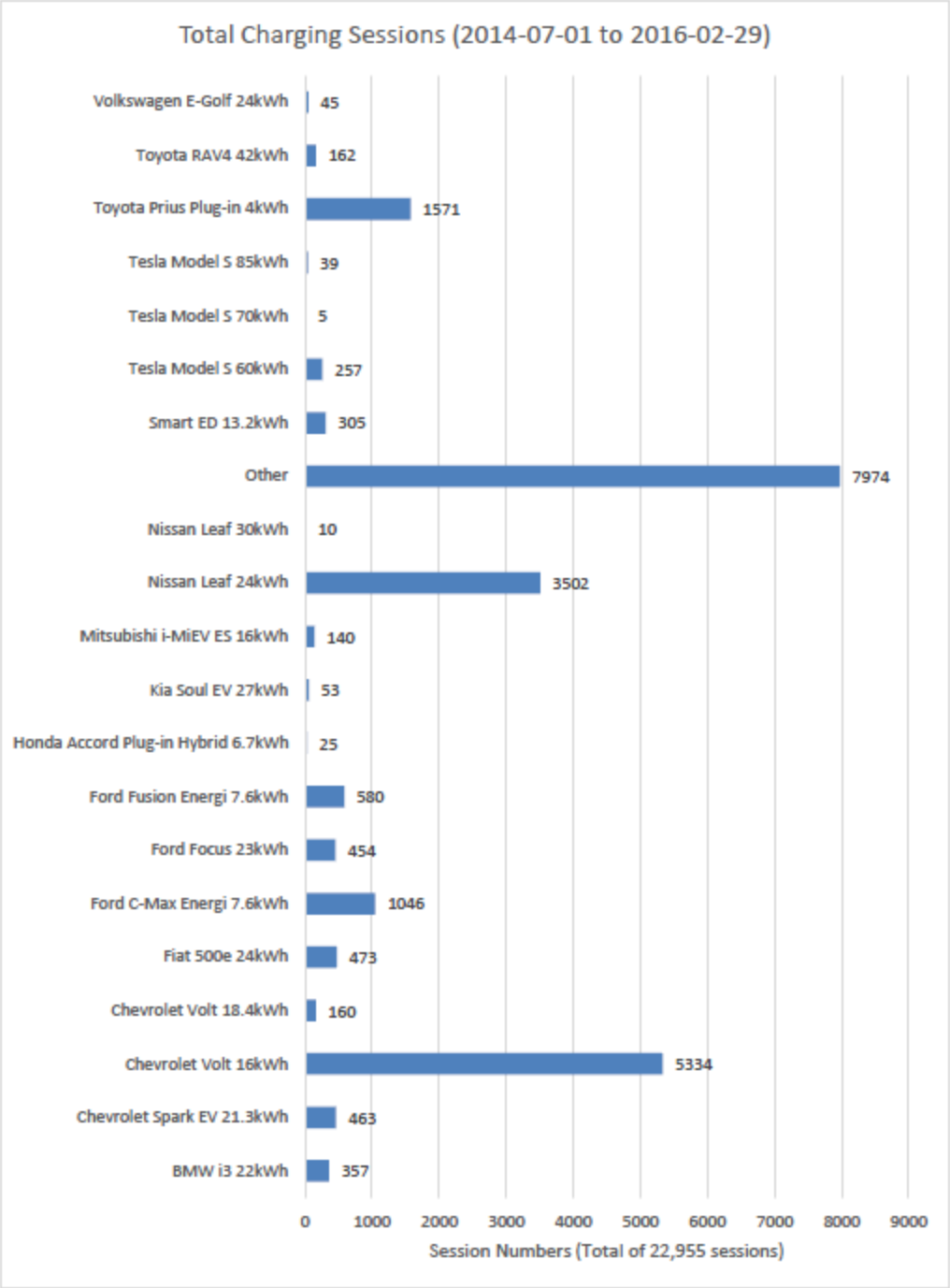


Figure 1: Total Charging Sessions (Jul 01 2014 – Feb 29 2016)

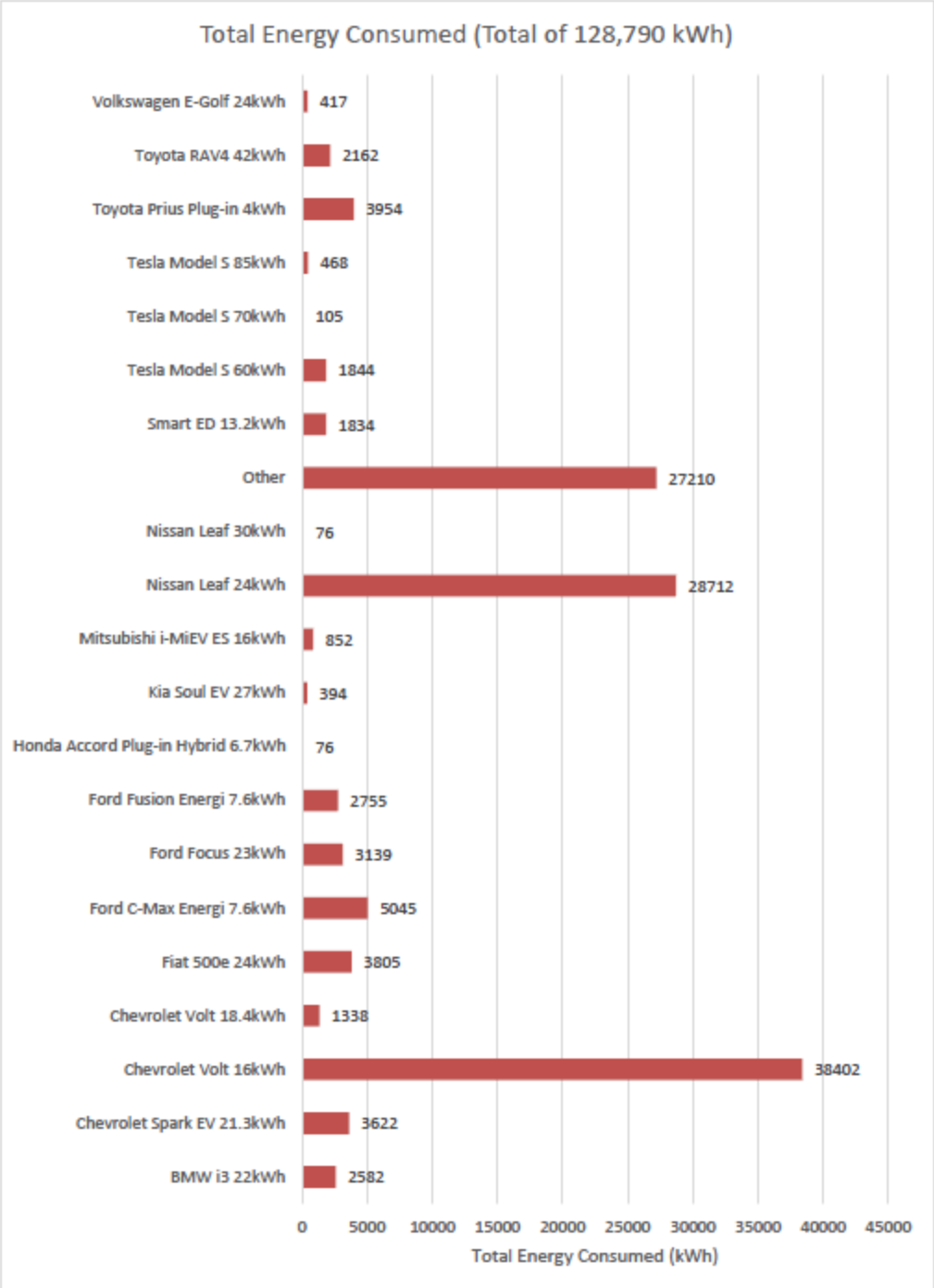


Figure 2: Total Energy Consumed

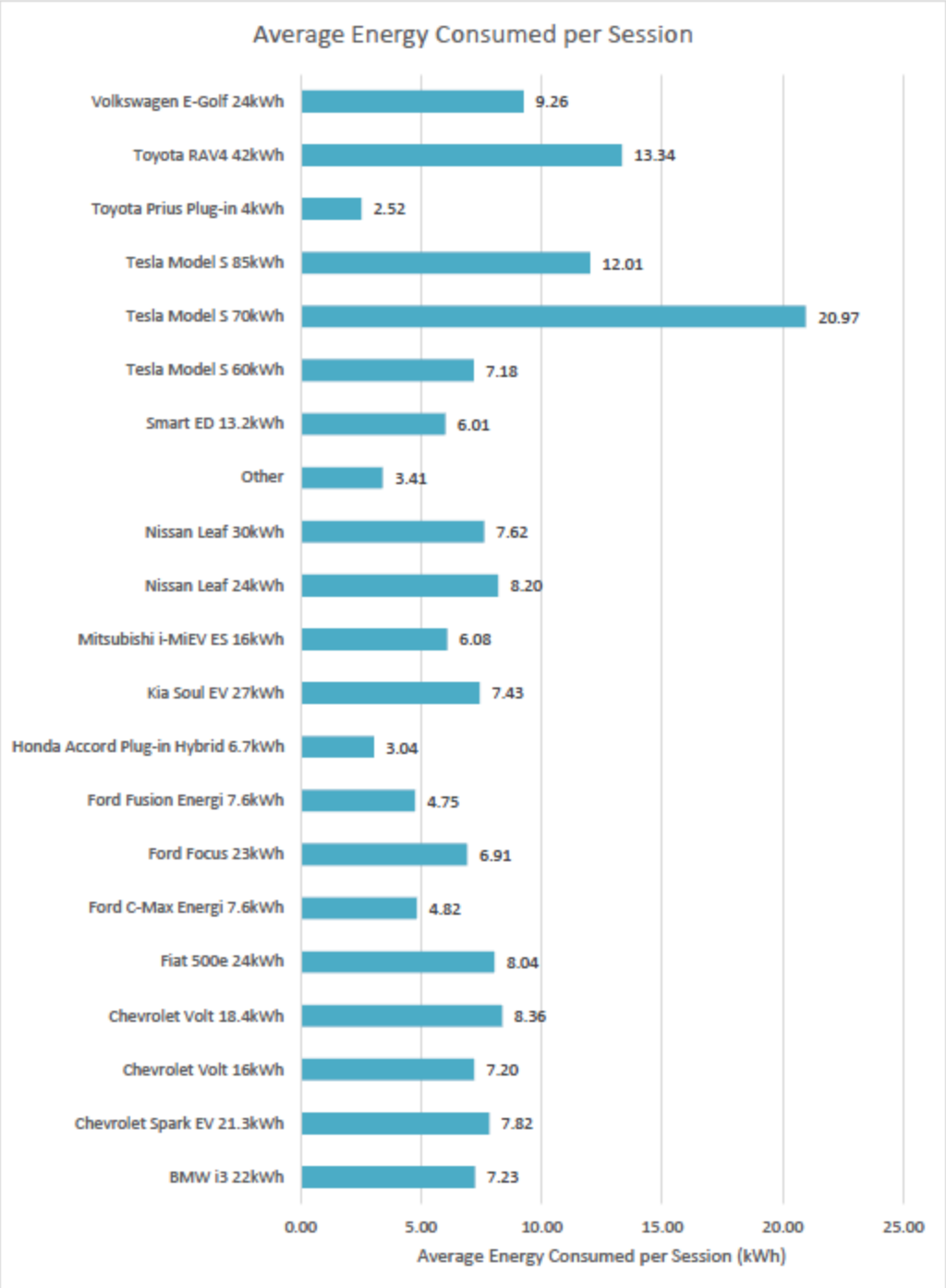


Figure 3: Average Energy Consumed per Session



Figure 4: Algorithm Closes Tesla's Charging Session

Charging Info between 10/15/2014 06:00:00 and 10/15/2014 17:00:05

Power Slot	User Name	Manufacturer	Model	Start Time	End Time	End	Ended By User	Charging Times	Energy Price	Energy Consumed	Charging Cost
1	ddralle	Chevrolet	Volt	10/15/2014 12:36:17 PM	10/15/2014 4:27:01 PM	✓	✓	6	11.00	2.7066kWh	$0.30
4	gadh	Tesla	Model S 60kWh	10/15/2014 1:26:19 PM	10/15/2014 3:06:02 PM	✓		5	15.00	1.0470kWh	$0.16



Figure 5: Charging Session on Oct 15 2014

Charging Info between 10/31/2014 06:00:00 and 10/31/2014 17:00:05

Power Slot	User Name	Manufacturer	Model	Start Time	End Time	End	Ended By User	Charging Times	Energy Price	Energy Consumed	Charging Cost
1	ddralle	Chevrolet	Volt	10/31/2014 11:34:03 AM	10/31/2014 11:39:52 AM	✓	✓	0	11.00	0.0000kWh	$0.00
2	mramirez44	Ford	Fusion Energi	10/31/2014 8:53:01 AM	10/31/2014 1:39:05 PM	✓		7	16.00	4.2550kWh	$0.68
2	mramirez44	Ford	Fusion Energi	10/31/2014 1:39:58 PM	10/31/2014 2:07:00 PM	✓		1	13.00	0.0010kWh	$0.00
2	mramirez44	Ford	Fusion Energi	10/31/2014 2:26:41 PM	10/31/2014 4:45:36 PM	✓		2	16.00	2.6970kWh	$0.43
4	gadh	Tesla	Model S 60kWh	10/31/2014 10:43:47 AM	10/31/2014 12:45:12 PM	✓		5	16.00	1.3950kWh	$0.22
4	wbin	Other	Other	10/31/2014 1:16:21 PM	10/31/2014 1:27:44 PM	✓		1	16.00	0.0000kWh	$0.00
4	wbin	Other	Other	10/31/2014 1:32:44 PM	10/31/2014 2:51:56 PM	✓		3	16.00	0.7710kWh	$0.12

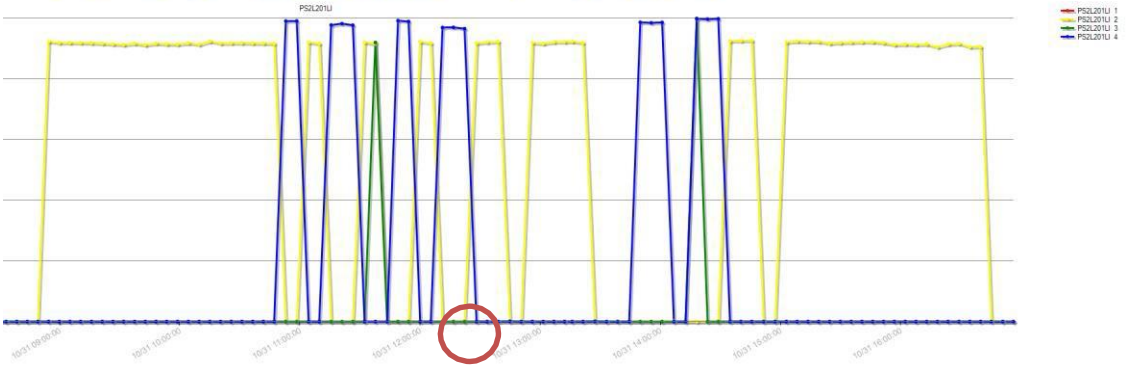


Figure 6: Charging Session on Oct 31 2014



Figure 7: Charging Session on Nov 3 2014

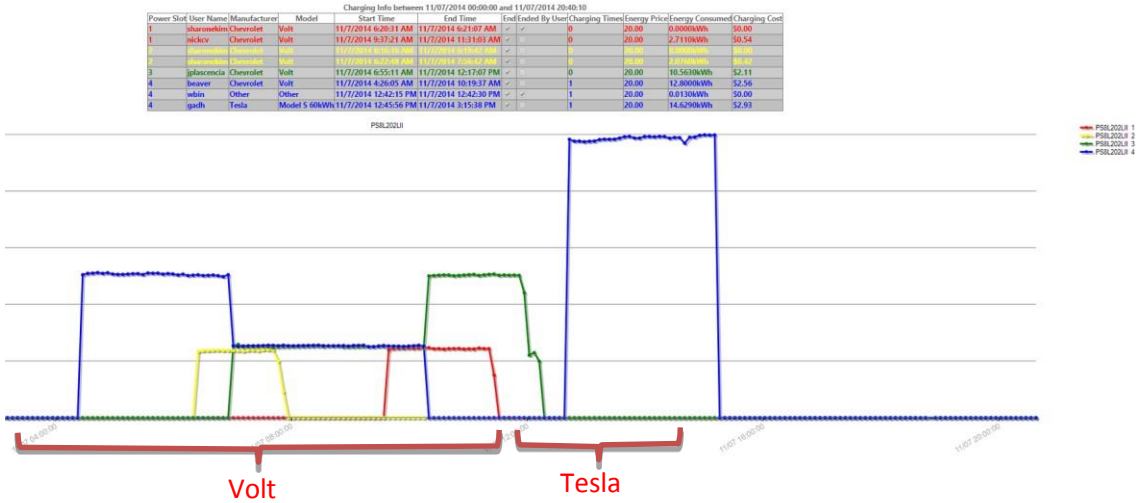


Figure 8: Comparison of Power Consumption Between Tesla and Chevy Volt

List of Reports Published under this Demo
None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo
None established.

Realized Impacts and Benefits to Date
None established.

Appendix AH UCLA TPR Use Case 12

Technology Performance Report (TPR)
Use Case (Demonstration) #12
June 25, 2016

Demo/Use Case Name: Local Grid Balancing and Management

Brief Description:

The purpose of this use case was to demonstrate the ability to monitor and to control loads to help manage grid instability. The loads controlled were mainly from EV charging stations.

Design Document Methodology

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. By utilizing non-critical loads, such as EV chargers and battery energy storage systems, the UCLA EV team demonstrated demand shedding and smoothing by sending demand response signals through the Super Control Center.

Demo responsibilities

This demonstration exhibited the utilization of a local distribution network with EV charging stations. Control of power consumption from the EV charging stations helped maintain the stability of a local grid. During peak consumption periods, the charging sessions could be delayed or re-scheduled until the network loading decreased or a dispatched generator's ramp-up period was completed. Shedding noncritical load during peak consumption periods could result in less fuel consumed by peaking generators, as well as delayed generation and transmission system upgrades. In addition, the levelization of the overall loading curve could be improved by transferring loads to off-peak periods.
This demonstration was performed in the SG Power Lab, where the charging station load was switched on and off in accordance with loading scenarios. This demonstration was performed by technicians supervised by engineering staff.

Demo steps and flow

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. EV Vitals & Scenario Data sent to Control Center
4. Control Center sends commands to Charging Station
5. Charging Station charges EV per commands
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data

7. EV informs Station charging is complete
8. Charging Station reports results of charge to Control Center
9. Charging Station inform operator results of charging session
10. Operator removes & stores Charging Cable
11. Charging Station resets for new charging session

Planned approach

28. Perform load shedding on various EV chargers
29. Monitor and evaluate data from EV chargers
30. Document and report on load balancing management

Final Used Methodology

Key changes in Demo design and justification

In the initial design, the management of DR signals was designated at the EV Control Center, in order to have direct access and control to the individual charging stations and EV. However, Super Control Center was built as an independent platform separate from the EV Control Center. The Super Control Center did not take direct control over specific EV charging nor received power data from individual charging stations. Simulating the role of electric utility, Super Control Center issued macro-scale DR signals to EV Control Center. Subsequently, EV Control Center made decisions regarding specific operations. As a result, Super Control Center observed resultant aggregated power data rather than monitoring individual station status or their management. This infrastructure facilitated future expansion of enrolled entities and reduced complexity for programming control algorithms in the SCC level. For a larger network with multiple EV Control Centers, each EV Control Center could own its individual management algorithm in microscopic scale to satisfy the signal from the Super Control Center. However, the original steps in the demonstration design were not been changed.

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- Battery Energy Storage System
- 137 EV Chargers
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification**"

Progress vs. success criteria

1. Charging Station records EV Vitals - **Complete**
2. Charging Station records Scenario Data - **Complete**
3. EV Vitals & Scenario Data sent to Control Center - **Complete**
4. Control Center sends commands to Charging Station - **Complete**

5. Charging Station charges EV per commands - **Complete**
6. On a periodic basis, Charging Station will report to Control Center status and accumulative charging data - **Complete**
7. EV informs Station charging is complete - **Complete**
8. Charging Station reports results of charge to Control Center - **Complete**
9. Charging Station inform operator results of charging session - **Complete**
10. Operator removes & stores Charging Cable - **Complete**
11. Charging Station resets for new charging session - **Complete**

Observations and Results

Observations and Results

In this report, the UCLA EV team successfully showed a system structure that was able to implement DR signals based on the maximum load predefined within each Parking Structure at UCLA. The system was designed to be compliant with the OpenADR standard as it received OpenADR requests with highest priority.

The system was versatile in terms of structure so it was easy for additional resources to join in and show related information. As the main function of the system, the SCC could implement a wide array of scheduling algorithms. The scheduling algorithm could be defined by user and will take care of the macroscopic scale of the energy management as the role of utility manager while leaving the microscopic management role to local EV control centers. This configuration allowed a flexible structure for further scaling up. The UCLA EV team tested the scalability with Virtual Devices. The team also discussed the reliability of the Control Center as it was a potential concern for actual implementation in industry.

For practical consideration, the Super Control Center ran DR for 2-4 times per month. The UCLA EV team showed one experiment where they suppressed one Parking Structure due to large energy consumption.

Lessons Learned

- An intermediate agent (middleware) was needed to aggregate and control a group of device so that upper-level EMS system such as SCC could successfully implement the commanding role in overall energy management
- The Smart EV charging stations may be able to respond to a turn off command in less than a minute (depending on the network connection), for the load shedding result initiated from SCC. To reach each individual EV charger, the process may take about 3 min.
- A frequent change of charging current on an EV charging station may result in malfunction on the EV charger and a manual re-start of the EV charger will be needed.

Best Practices

The UCLA EV team learned that for a complicated and distributed system, the best practice for a control EMS is to only manage a macroscopic view at the PS level while giving EV Control

Center its own operation ability for microscopic adjustment over each charging station. UCLA SMERC Team was still working on determining the best automatic demand response operation when additional data was received toward the end of this project.

Results of Data Collection

- The UCLA EV team collected numerous data points from 136 Level 1 and Level 2 EV chargers for 5 months. These data points include the timestamp, active power of the Level 3 EV Charger, active power of all EV chargers on the UCLA campus separated by parking structure, and the total active power of all EV stations.

Data Collection Summary

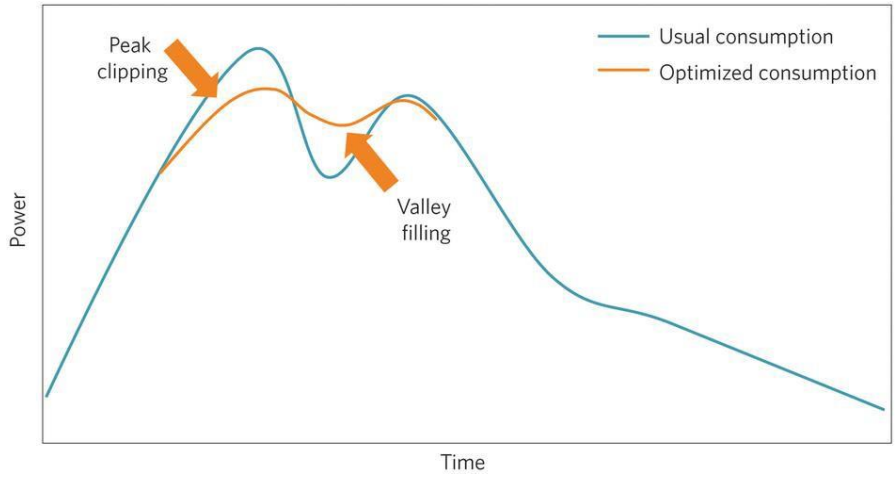


Figure 1: Demand Shedding and Smoothing

Location	Voltage	Connector type	Plug Points	Max Power (kW)
PS 9 Level 4	120 V	NEMA 5-15	4	1.8
PS 9 Level 6	120 V	NEMA 5-15	4	1.8
PS 8 level 2 South	208 V	J1772	4	6.6
PS 8 level 2 North	208 V	J1772	4	6.6
PS 2 level 2	120 V	NEMA 5-15	4	1.8
PS 3 level 4	120 V	NEMA 5-15	4	1.8
PS 3 level 2	208V	J1772	4	6.6
PS 4 Box 1	208 V	J1772	4	6.6
PS 4 Box 2	208 V	J1772	4	4.2
PS 2	208 V	J1772	4	6.6
DCFC PS 4	480 V	CHAdeMO	1	50
Total			41	94.4

Table 1: Participating Charging Stations

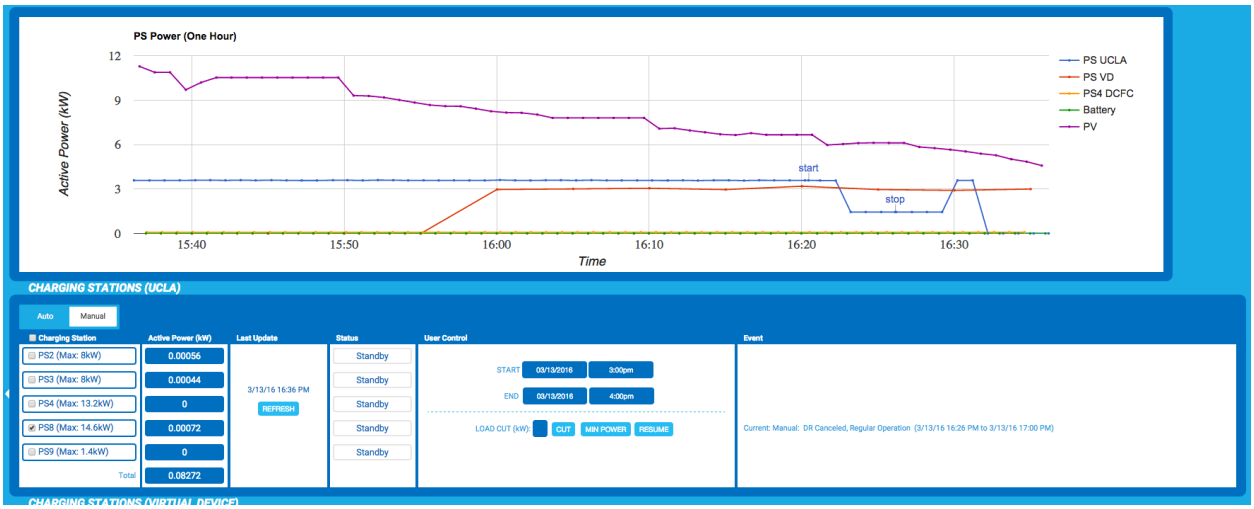


Figure 2: SCC GUI Showing DR Start and Stop Point

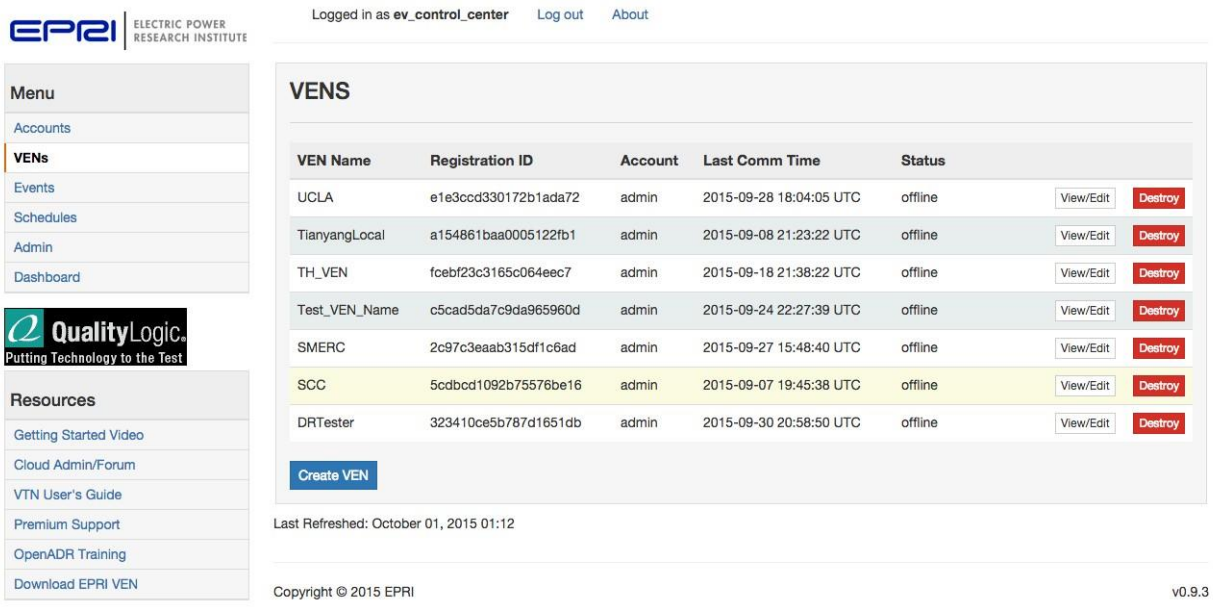


Figure 3: VEN Management Interface

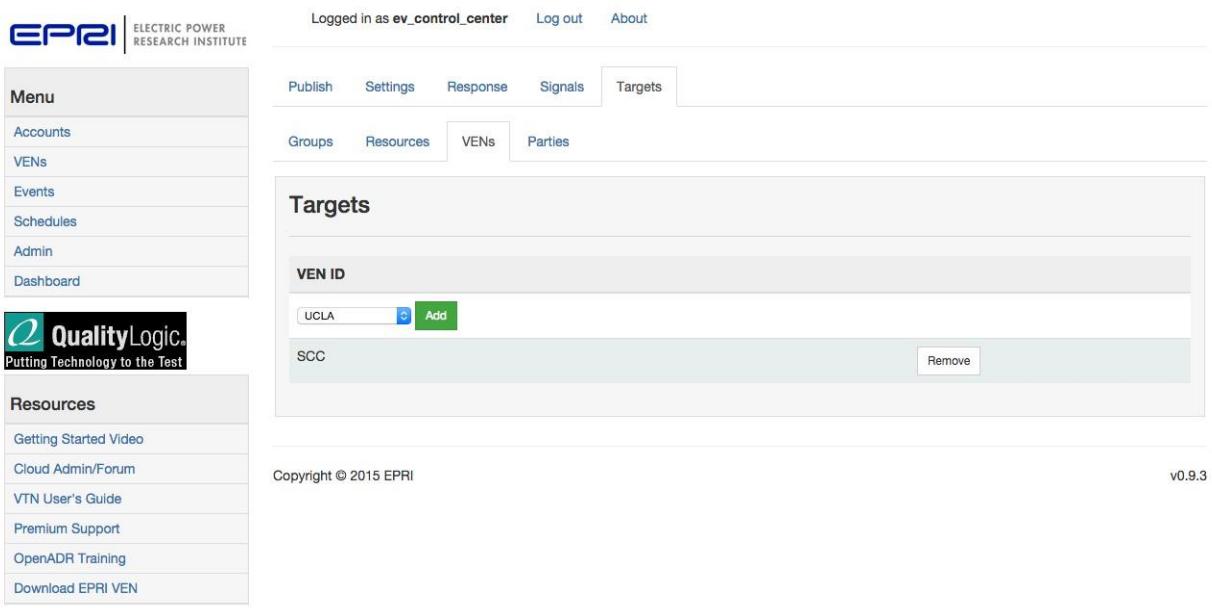


Figure 4: Add Target VEN in DR Event

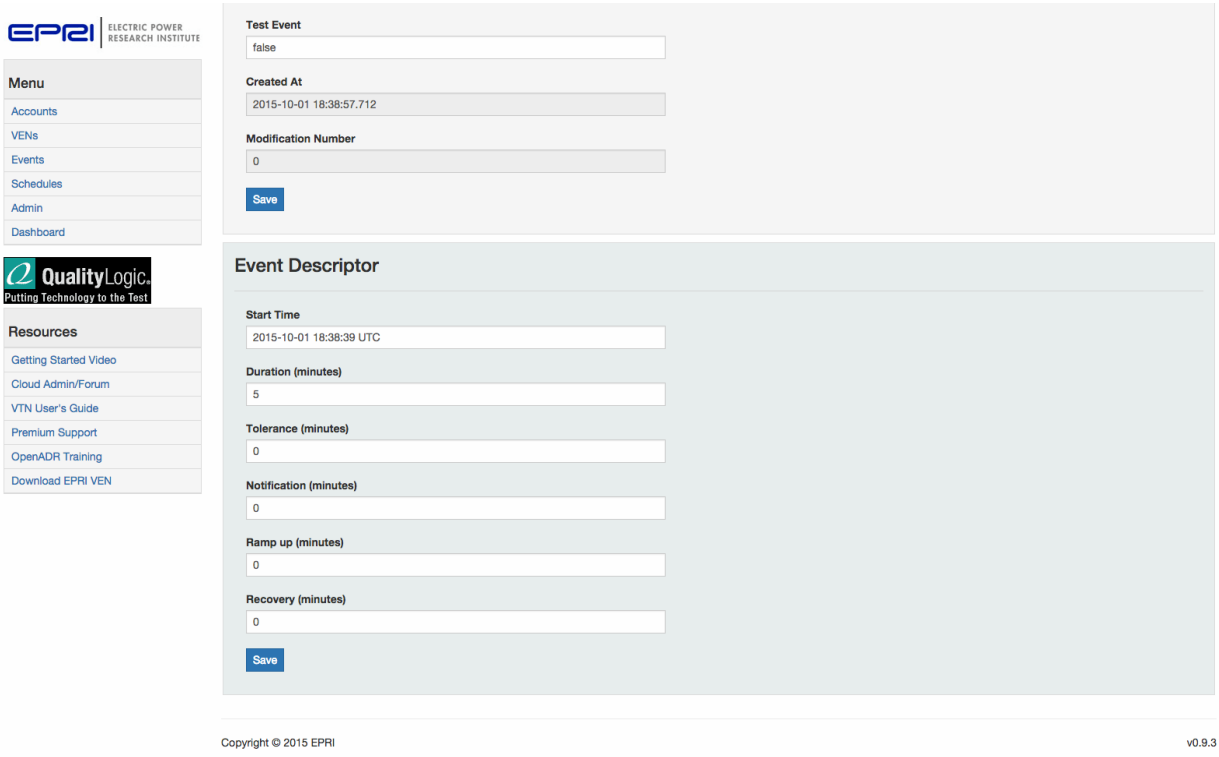


Figure 5: Configure DR Event Specifications

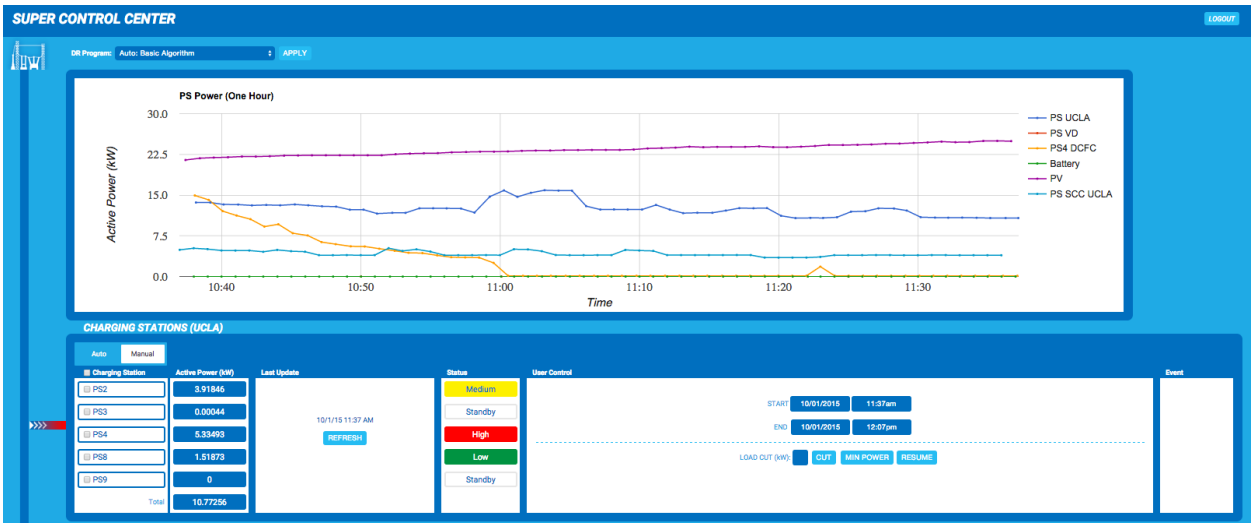


Figure 6: SCC Interface Before OpenADR Signal

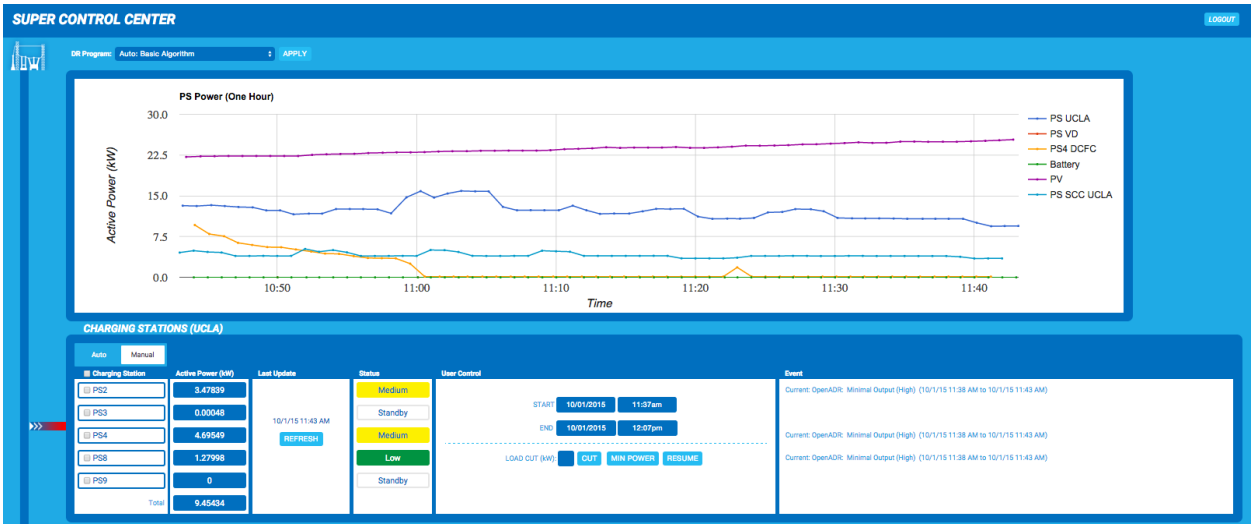


Figure 7: SCC Interface during OpenADR Signal

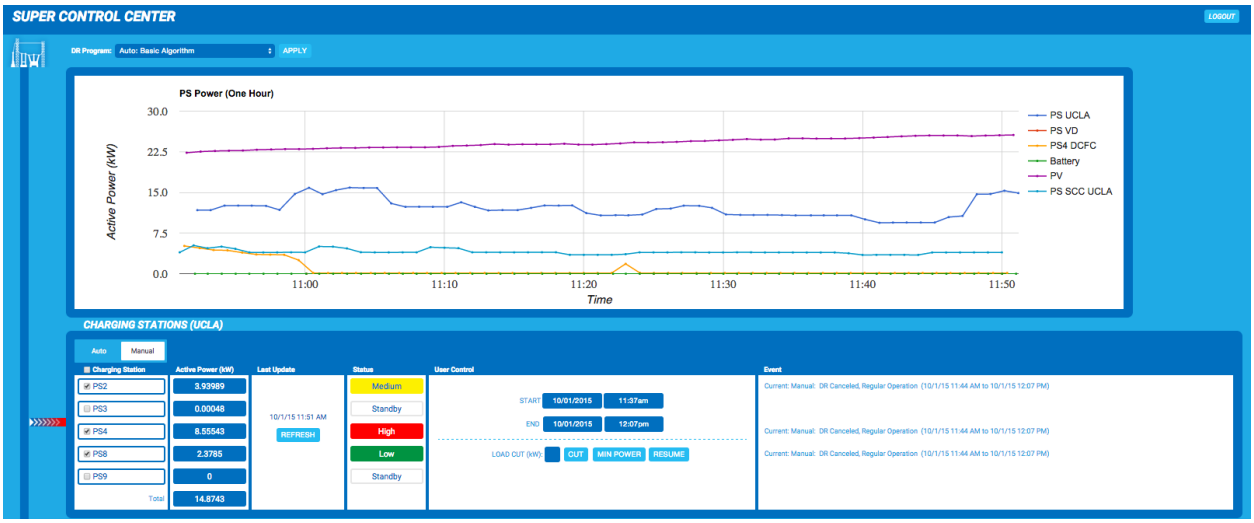


Figure 8: SCC Interface After OpenADR Signal

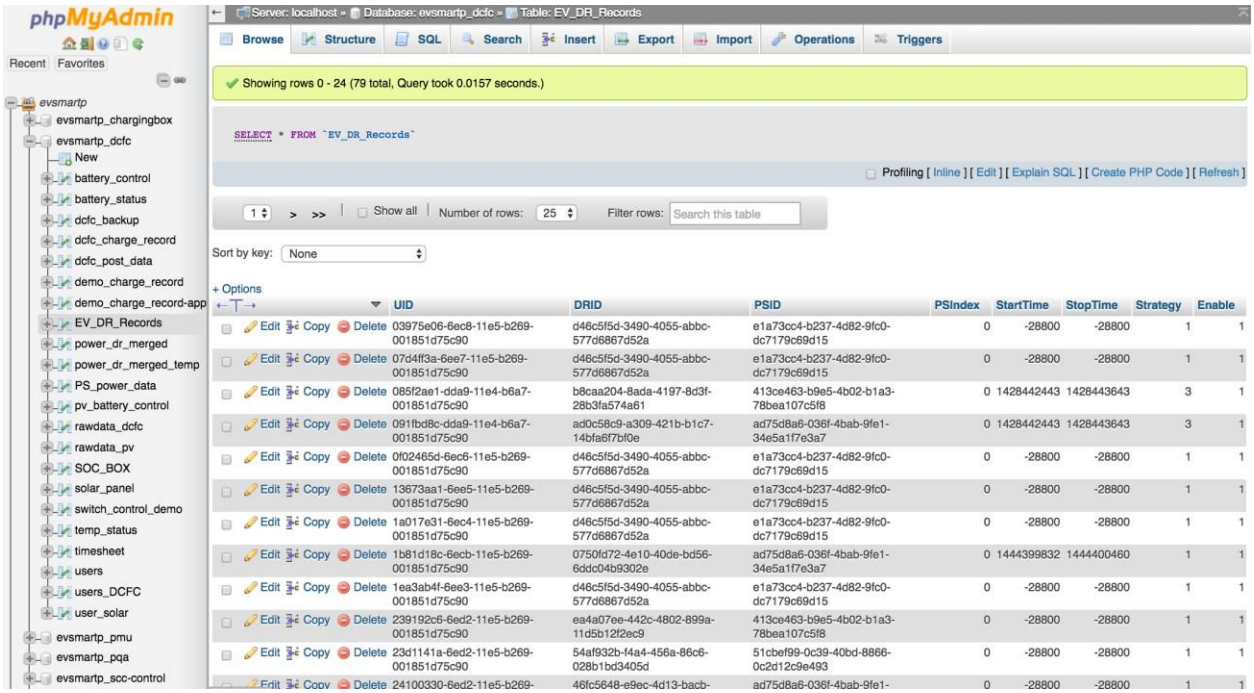


Figure 9: PhPMyAdmin Database Manager

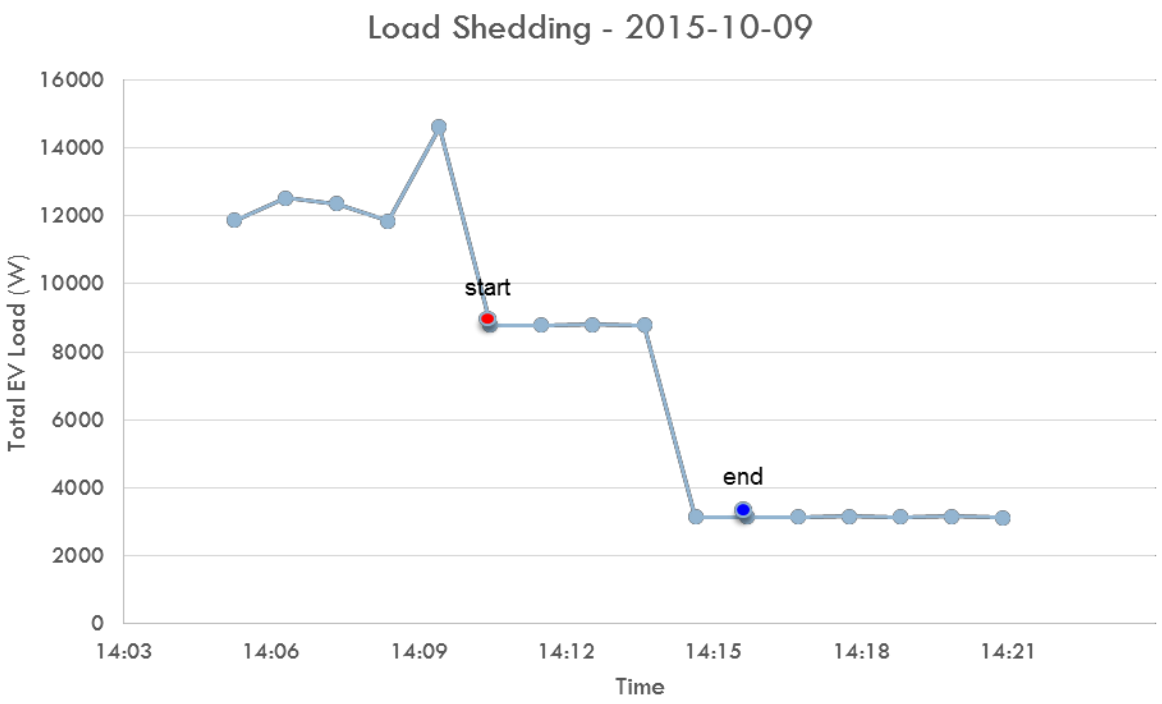


Figure 10: Manual Load Shedding Oct 09 2015

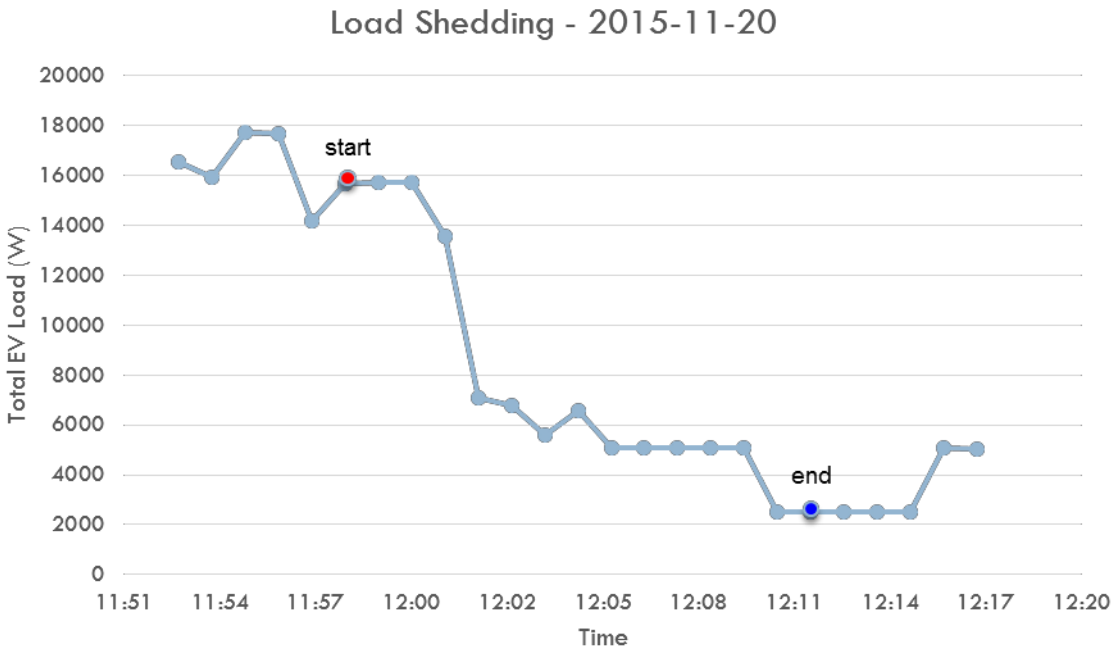


Figure 11: Manual Load Shedding Nov 20 2015

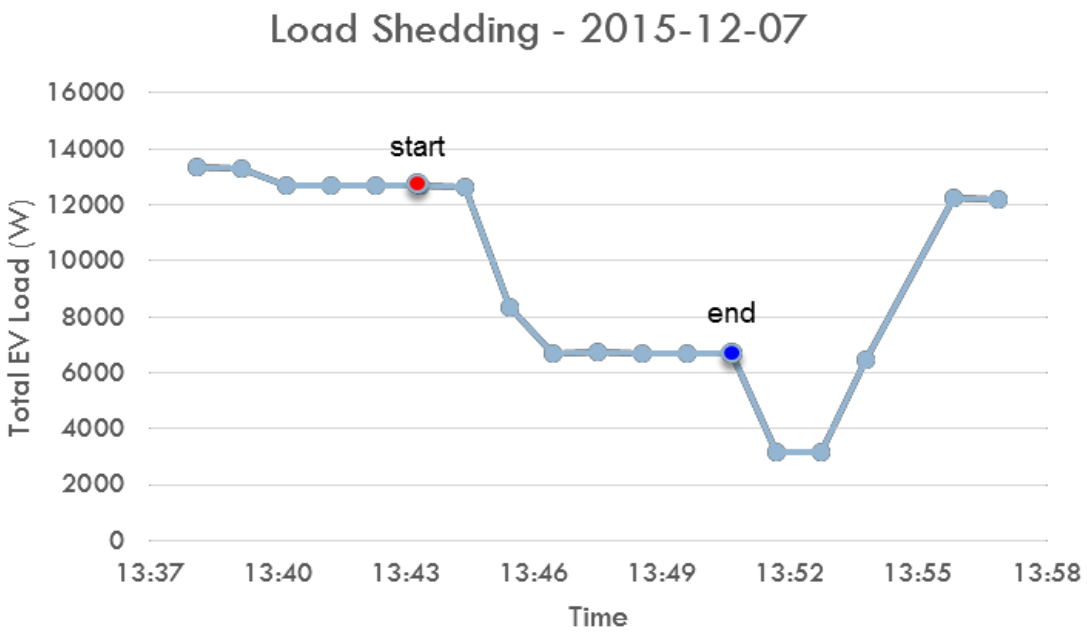


Figure 12: Manual Load Shedding Dec 07 2015

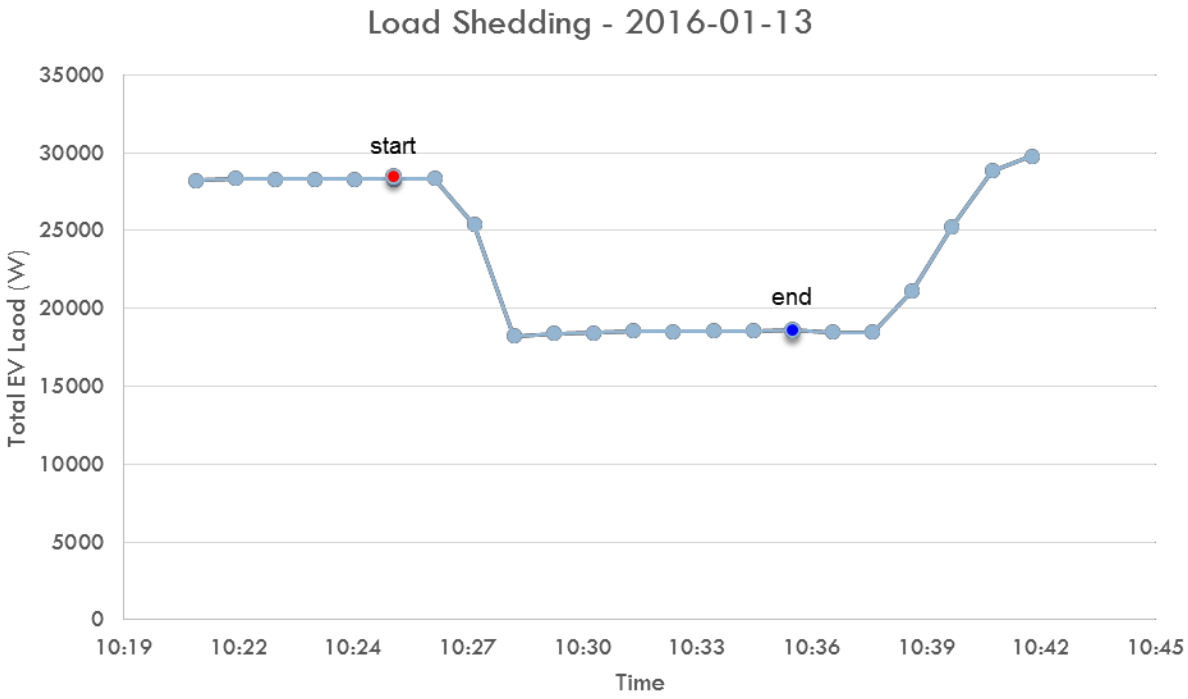


Figure 13: Manual Load Shedding Jan 13 2016

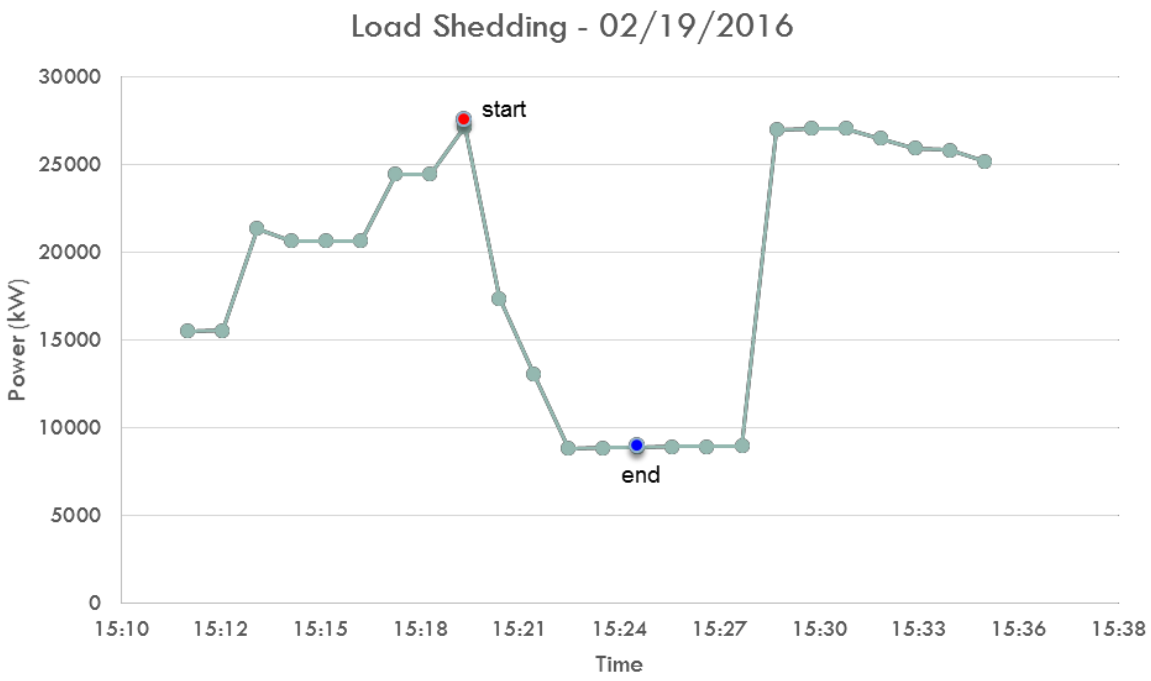


Figure 14: Automatic Maximum Load Shedding Feb 19 2016 (note: Values in Vertical axis are in watt)

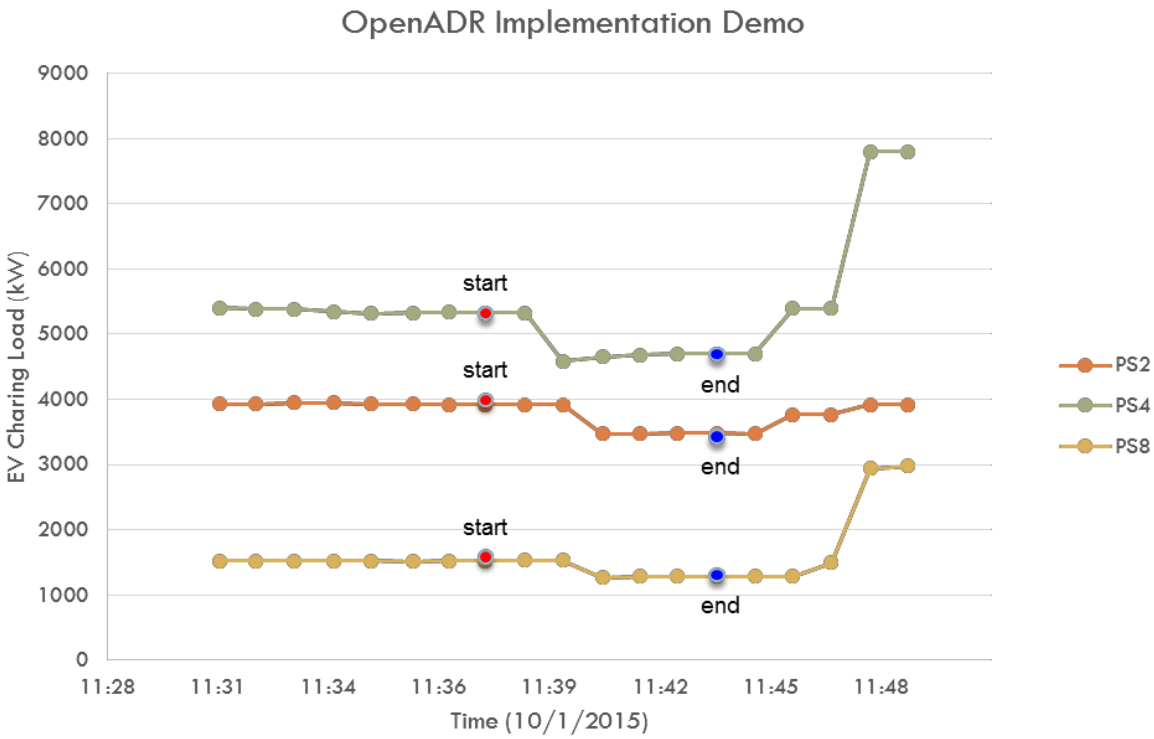


Figure 15: Limited OpenADR Data Collection Results (note: Values in Vertical axis are in watt)

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

- By utilizing the ability to shed load automatically or manually, utilities will be able to save generation costs by utilizing EVs to help reduce peak demand.

Realized Impacts and Benefits to Date

No impact.

Appendix AI UCLA TPR EV Use Case 13

Technology Performance Report (TPR)
Use Case (Demonstration) #13
June 25, 2016

Demo/Use Case Name: Community Storage of EV Batteries and External Storage

Brief Description:

The purpose of this use case was to demonstrate and research the use of EV batteries and battery external storage on the grid. The UCLA EV team demonstrated four different scenarios for this use case: BESS used to regulate the voltage, BESS used to smooth solar, BESS used to cut the EV Charging peak demand, and normal operation.

Design Document Methodology

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. Additionally, the team developed and installed a 62 kWh capacity battery storage system to use for this use case. With this setup, the UCLA EV team demonstrated four different scenarios: voltage regulation and control active and reactive power, solar smoothing, cutting EV charging peak demand, and normal operation (charging and discharging the energy storage system on a regular basis).

Demo responsibilities

This demonstration displayed the status of all EV chargers to indicate whether and when charging was occurring. This demonstration took place at the SG Power Lab, Various Demo Sites, and the SG EV Control Center, and was executed primarily by UCLA personnel. The

demonstration provided detailed, on-demand charger information that indicated both the status of the charger and a regular transmittal of charging duration. The EV charger communicated directly with the SG EV Control Center through an application interface provided by the charger vendors, as well as additional metering devices, where feasible.

The EV project team installed charging stations from various vendors at UCLA & LADWP parking structures. These charging stations included Level 1, Level 2 and Level 3 charging.

However, as most charging stations use proprietary communication protocols, the EV Team may be unable to obtain detailed user data and fully control the charging operations from the SG EV Control Center. Due to this limitation, the UCLA EV team designed and developed an open-architecture charging station that supported the data collection and circuit control of this project. These charging stations were implemented to provide the following functions:

6. Open architecture to collect user and vehicle profile, kW, usage history, etc.
7. Battery aggregation to provide dynamic charging scheme based on various inputs
8. Level 1 and Level 2 charging support
9. Safety and security factors in the design
10. Backfill integration

The UCLA EV team created an interface with commercial-off-the-shelf chargers to collect charger data to allow the SG EV Control Center to monitor all chargers installed during this project. The SG EV Control Center provided a visualization portal to monitor the status of all chargers with a graphical interface to indicate the geographical location of the charger and its usage.

Demo steps and flow

A. Grid used to charge CES
   1. CES receives signal from Control Center to charge
   2. CES records CES vitals
   3. CES vitals sent to Control Center
   4. On periodic basis, CES will report to Control Center status and accumulative charging data
   5. CES informs Control Center charging is complete
   6. CES reports results of charge to Control Center
B. CES used to charge EV
   1. Charging Station records EV Vitals
   2. Charging Station records Scenario Data
   3. EV Vitals & Scenario Data sent to Control Center
   4. CES records CES vitals
   5. CES vitals sent to Control Center
   6. Control Center sends commands to Charging Station (to charge) & CES (to discharge)
   7. On periodic basis, CES will report to Control Center status and accumulative discharging data

8. On periodic basis, EV will report to Control Center status and accumulative charging data
9. CES informs Control Center SOC is at minimum value **or** EV informs Control Center charging is complete
10. CES reports results of discharge to Control Center
11. EV reports results of charge to Control Center

Planned approach

31. Develop and install Battery Storage System
32. Monitor and Evaluate Data from Battery Storage System tests
33. Document and report on Community Storage on EV Vehicles and Battery Storage

Final Used Methodology

Key changes in Demo design and justification

The UCLA EV team determined that the battery energy storage system could be used in a more active manner to help improve the EV charging load, power quality, and PV smoothing. Therefore, the UCLA EV team expanded on the original demonstration design to the following:

A. BESS is used to regulate the voltage
   1. Local control frequently send the signal to check the availability of BESS
   2. Local control frequently send the signal to check the availability of GTI
   3. BESS and GTI send back the ready status signal
   4. BESS records BESS vitals
   5. BESS vitals sent to Local Controller
   6. On periodic basis, BESS will report its status to local controller and accumulative data
   7. Measurement unit send periodically the voltage information of the grid to local controller
   8. Local controller send the reactive power control signal to GTI
   9. GTI operates in leading or lagging mode
   10. Local controller stores all the data

B. BESS is used to smooth the solar
   1. Local control frequently send the signal to check the availability of BESS
   2. Local control frequently send the signal to check the availability of GTI
   3. BESS and GTI send back the ready status signal
   4. BESS records BESS vitals
   5. BESS vitals sent to Local Controller
   6. On periodic basis, BESS will report its status to local controller and accumulative data
   7. Control center send periodically the power information of solar to local controller
   8. Local controller calculate and generate the appropriate reaction signal
   9. Local controller send the active power control signal to GTI
   10. GTI operates charging or discharging mode
   11. Local controller stores all the data

C. BESS is used to cut the EV charging peak demand

1. Local control frequently send the signal to check the availability of BESS
2. Local control frequently send the signal to check the availability of GTI
3. BESS and GTI send back the ready status signal
4. BESS records BESS vitals
5. BESS vitals sent to Local Controller
6. On periodic basis, BESS will report its status to local controller and accumulative data
7. Control center send periodically the DCFC power information to local controller
8. Local controller calculate and generate the appropriate reaction signal
9. Local controller send the active power control signal to GTI
10. GTI operates in charging or discharging mode
11. Local controller stores all the data

D. Normal operation

1. Local control frequently send the signal to check the availability of BESS
2. Local control frequently send the signal to check the availability of GTI
3. BESS and GTI send back the ready status signal
4. BESS records BESS vitals
5. BESS vitals sent to Local Controller
6. On periodic basis, BESS will report its status to local controller and accumulative data
7. Local Control periodically check the status of battery module includes voltage, temperature, SOC, SOH, and charging and discharging current limits, etc.
8. Local controller calculate and generate the appropriate reaction signal
9. Local controller send the active power control signal to GTI
10. GTI operates in charging or discharging mode
11. Local controller stores all the data

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- PV Array
- Battery Energy Storage System
- 136 EV Chargers
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification**"

Progress vs. success criteria

A. BESS is used to regulate the voltage

1. Local control frequently send the signal to check the availability of BESS - **Complete**

2. Local control frequently send the signal to check the availability of GTI - **Complete**
3. BESS and GTI send back the ready status signal - **Complete**
4. BESS records BESS vitals - **Complete**
5. BESS vitals sent to Local Controller - **Complete**
6. On periodic basis, BESS will report its status to local controller and accumulative data - **Complete**
7. Measurement unit send periodically the voltage information of the grid to local controller - **Complete**
8. Local controller send the reactive power control signal to GTI - **Complete**
9. GTI operates in leading or lagging mode - **Complete**
10. Local controller stores all the data - **Complete**

B. BESS is used to smooth the solar

1. Local control frequently send the signal to check the availability of BESS - **Complete**
2. Local control frequently send the signal to check the availability of GTI - **Complete**
3. BESS and GTI send back the ready status signal - **Complete**
4. BESS records BESS vitals - **Complete**
5. BESS vitals sent to Local Controller - **Complete**
6. On periodic basis, BESS will report its status to local controller and accumulative data - **Complete**
7. Control center send periodically the power information of solar to local controller - **Complete**
8. Local controller calculate and generate the appropriate reaction signal - **Complete**
9. Local controller send the active power control signal to GTI - **Complete**
10. GTI operates charging or discharging mode - **Complete**
11. Local controller stores all the data - **Complete**

C. BESS is used to cut the EV charging peak demand

1. Local control frequently send the signal to check the availability of BESS - **Complete**
2. Local control frequently send the signal to check the availability of GTI - **Complete**
3. BESS and GTI send back the ready status signal - **Complete**
4. BESS records BESS vitals - **Complete**
5. BESS vitals sent to Local Controller - **Complete**
6. On periodic basis, BESS will report its status to local controller and accumulative data - **Complete**
7. Control center send periodically the DCFC power information to local controller - **Complete**
8. Local controller calculate and generate the appropriate reaction signal - **Complete**
9. Local controller send the active power control signal to GTI - **Complete**
10. GTI operates in charging or discharging mode - **Complete**
11. Local controller stores all the data - **Complete**

D. Normal operation

1. Local control frequently send the signal to check the availability of BESS - **Complete**
2. Local control frequently send the signal to check the availability of GTI - **Complete**
3. BESS and GTI send back the ready status signal - **Complete**
4. BESS records BESS vitals - **Complete**

5. BESS vitals sent to Local Controller - **Complete**
6. On periodic basis, BESS will report its status to local controller and accumulative data - **Complete**
7. Local Control periodically check the status of battery module includes voltage, temperature, SOC, SOH, and charging and discharging current limits, etc. - **Complete**
8. Local controller calculate and generate the appropriate reaction signal - **Complete**
9. Local controller send the active power control signal to GTI - **Complete**
10. GTI operates in charging or discharging mode - **Complete**
11. Local controller stores all the data - **Complete**

Observations and Results

Observations and Results

In this report, four main applications of battery storage system were investigated. In the first scenario, the Battery Energy Storage System (BESS) was employed to improve the voltage regulation. Voltage variation due to uncontrollable nature of PVs and EVs could have a direct impact on the operation of load tap changers, voltage-controlled capacitor banks, and line voltage regulators, which might cause additional step-voltage changes. Based on the delays (30-90s) in the control of the existing devices, minute-based step-voltage variations might be experienced. In addition, more frequent operation of these devices led to more maintenance requirements, which consequently made the expected life cycle of these devices short. In this case, the battery storage system was employed for voltage regulation of the distribution system by controlling the GTI reactive power. The results obtained from active and reactive power control was compared with reactive power control. It was shown that in the distribution system controlling the active power was also important for voltage regulation. The experiment performed on 02/16/2016-from 17:07 to 17:32 was the best practice for this scenario which employed both active and reactive power control for voltage regulation.

In scenario 2, the application of the BESS for solar smoothing was studied. As PV penetration increased beyond certain level, the fluctuations of PV power would adversely affect the operation of power system. Thus, a power system that depended entirely upon multiple renewable energy sources could be unreliable. Specifically, for very fast fluctuations, the power system operators had an extremely limited response capacity and, if the fluctuations exceed the permitted limits, there was a risk of a complete power system failure. In fact, some countries were currently working on grid codes that take this problem into account. This risk was particularly significant in a weak distribution grid with a high PV penetration rates, such as islands. The experiment performed on 01/07/2016 during 15:06:26 till 16:06:38 was the best outcome of this scenario during this period. In this experiment, a new filtering approach including prediction technique was developed to improve the solar fluctuation. The root-mean- square deviation (RMSD) or root-mean-square error (RMSE) criterion showed that this approach was damping the fluctuation of solar by 86%.

In the third scenario, the BESS was utilized to cut the peak demand of DCFC. It was shown that the battery storage system could effectively distribute the DCFC demand over the time and

reduce the grid power demand. The experiment run on 01/27/2015 during 14:01:40 to 16:23:04 was the best practice for cutting the demand scenario.

Finally, in the last scenario, the normal operation of battery storage system during charging and discharging was demonstrated and the variation of cell temperature. SOC and DC voltage were shown.

At the end, the success criteria of use case number 13 (Community Storage of EV Batteries and External Storage) was that all BESS devices & Charging Stations within Use Case scenario must report status and consumption to Control Center. The obtained results showed that BESS, DCFC, solar, and AC meter were reporting their status with high frequency. The BESS reported a wide range of parameters every 2 seconds which included date and time, DC voltage, DC current, Inverter active and reactive power, DC power, SOC, SOH, max and min cell temperature, and max and min cell Voltages. The solar and DCFC reported their generation and consumption power, respectively, every minute. The AC grid voltage was captured every 2 seconds. Therefore, the obtain results prove the success of this use case.

Lessons Learned

- The fluctuations of PV power would adversely affect the operation of power system. This risk was particularly significant in a weak distribution grid with a high PV penetration rates, such as islands.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected numerous data points from the battery energy storage system for October 2015, December 2015, January 2016, and February 2016. These data points include the timestamp, DC voltage, DC current, inverter active power, inverter reactive power, state of charge, maximum temperature, minimum temperature, maximum cell voltage, minimum cell voltage, AC voltage and mode of operation.

Data Collection Summary

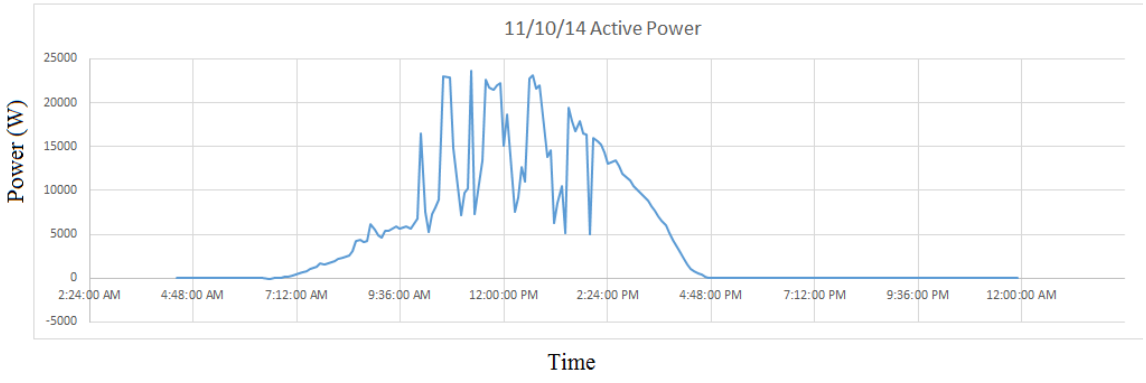


Figure 1: Power Fluctuation of PV on Nov 10 2014

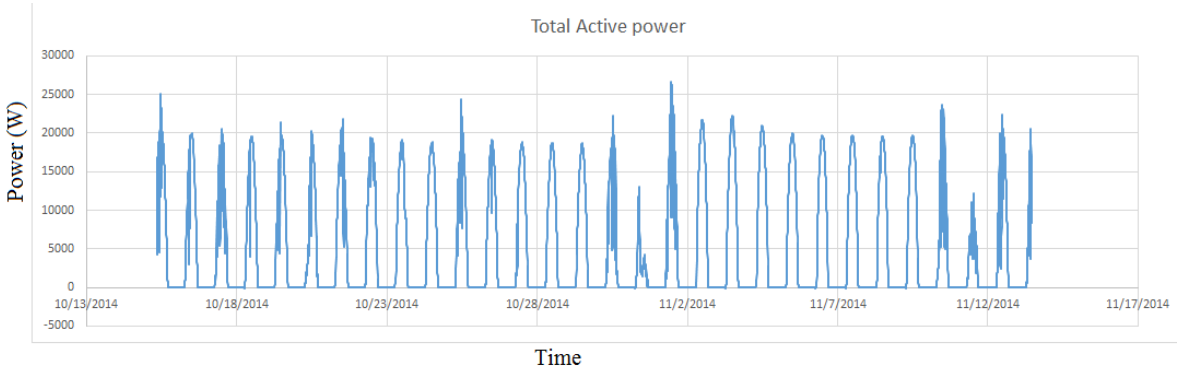


Figure 2: Power Fluctuation of PV from Oct 15 2014 to Nov 14 2014

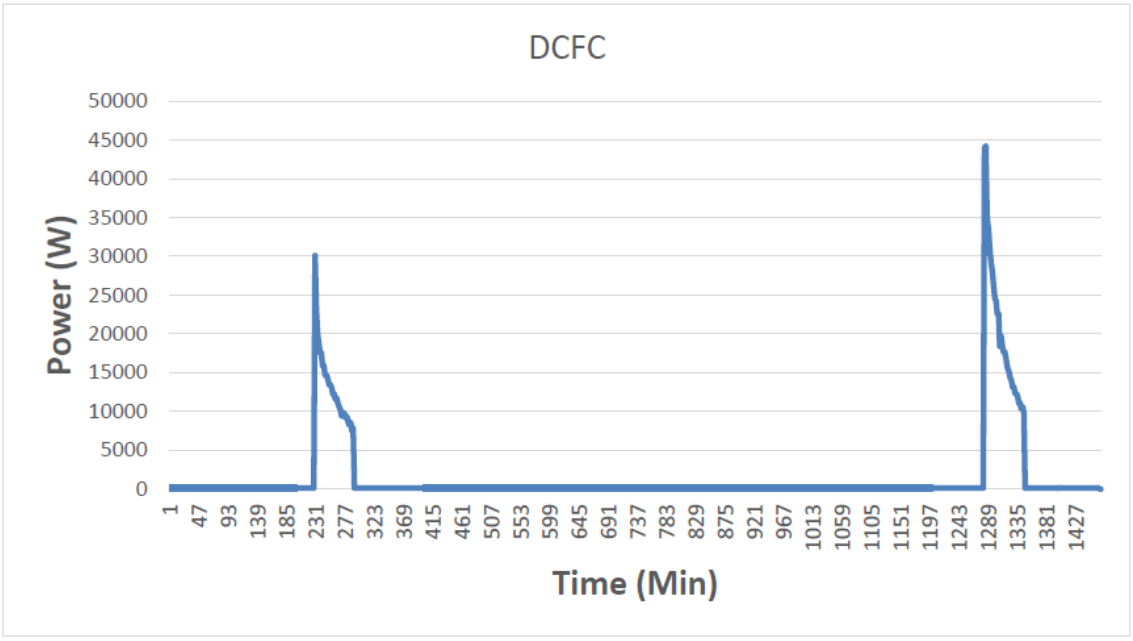


Figure 3: Peak of Power Demand During EVs Charging

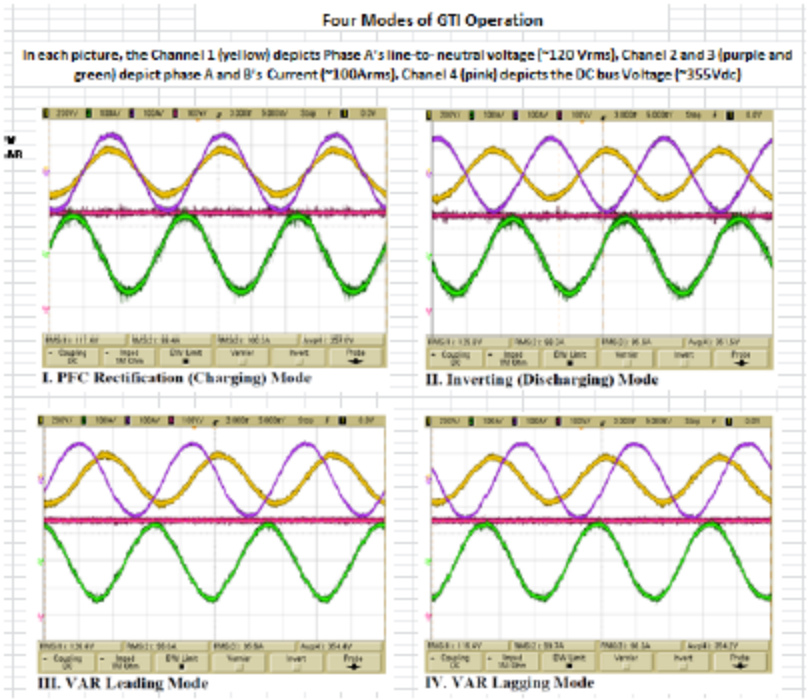


Figure 4: Four Modes of GTI Operation

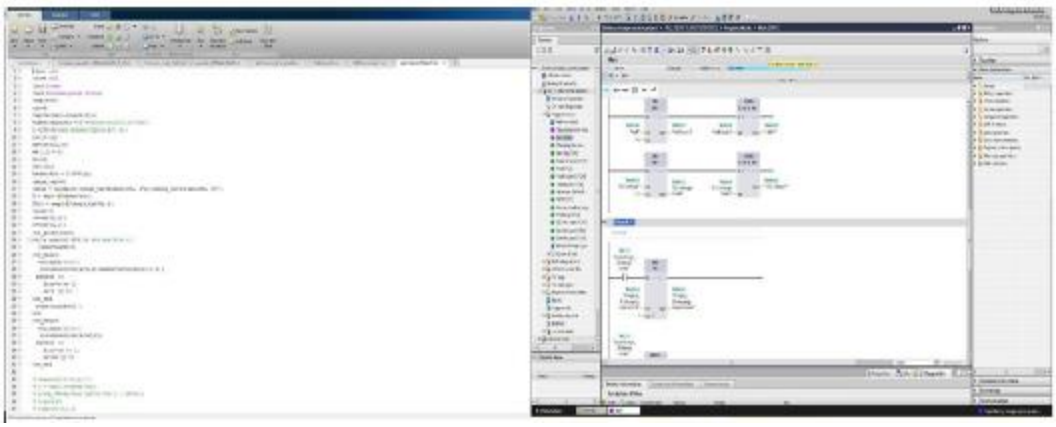


Figure 5: Software Interface for Battery Energy Storage System Monitoring and Control

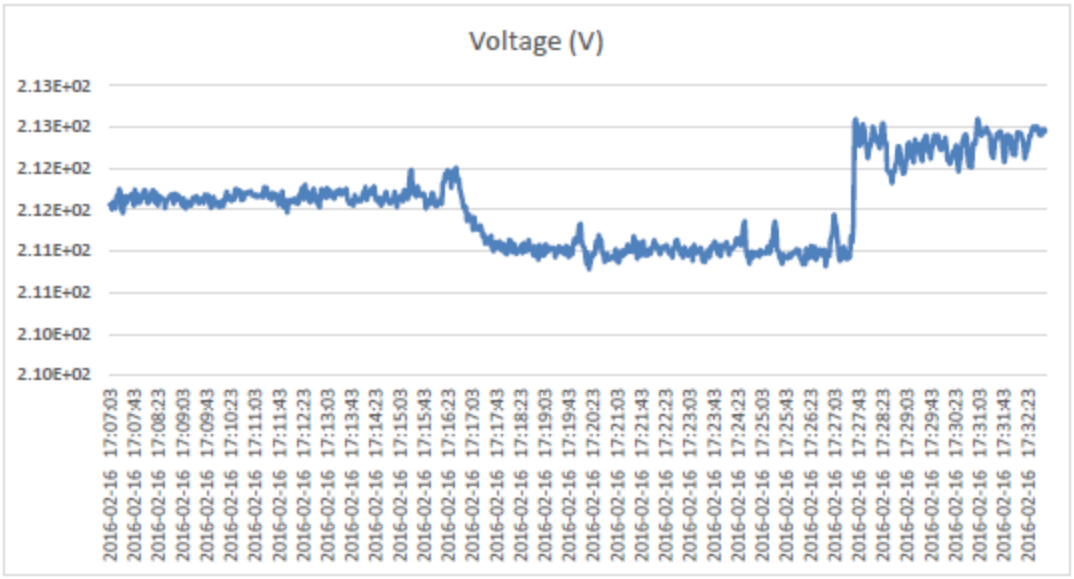


Figure 6: Grid Voltage Profile for First Experiment

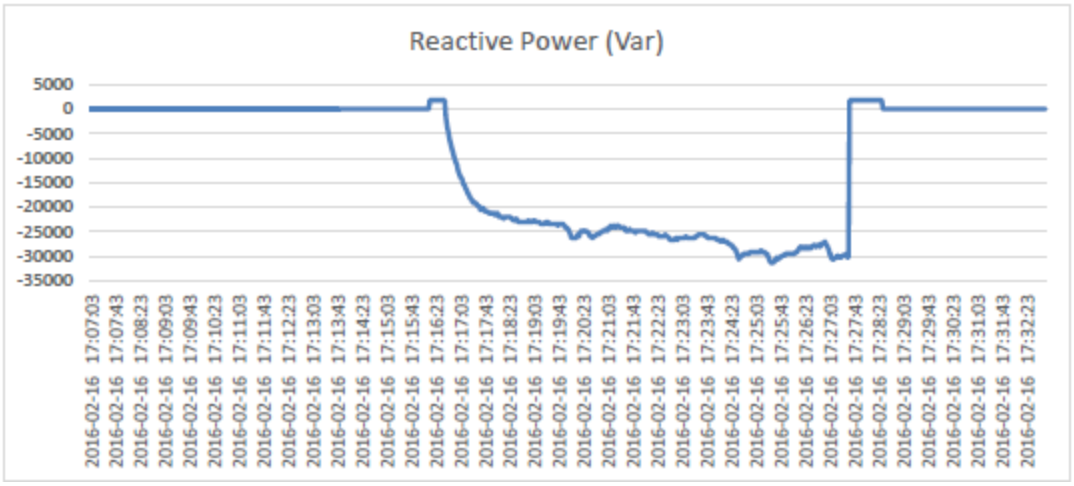


Figure 7: GTI Reactive Power for First Experiment

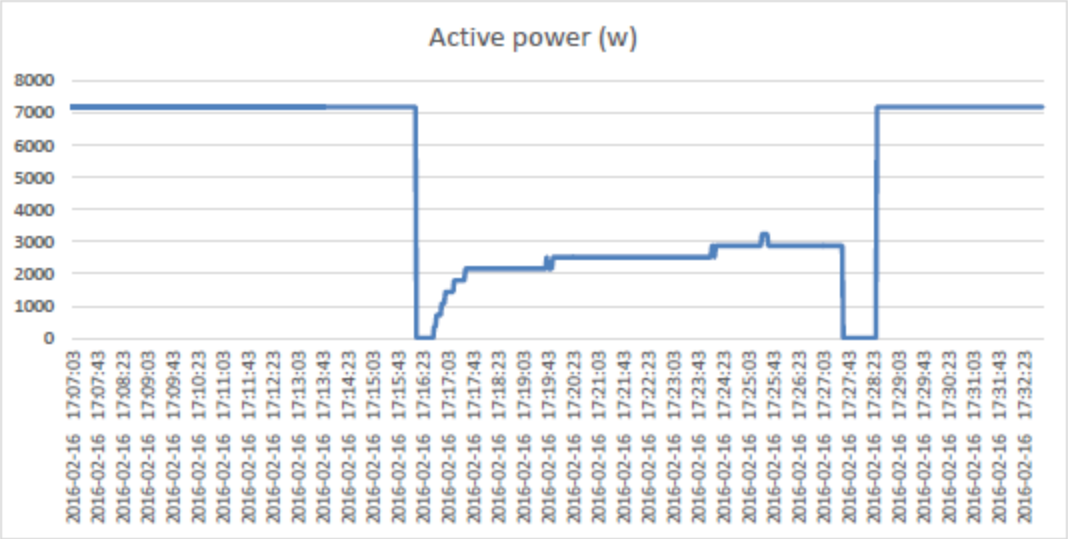


Figure 8: GTI Active Power for First Experiment

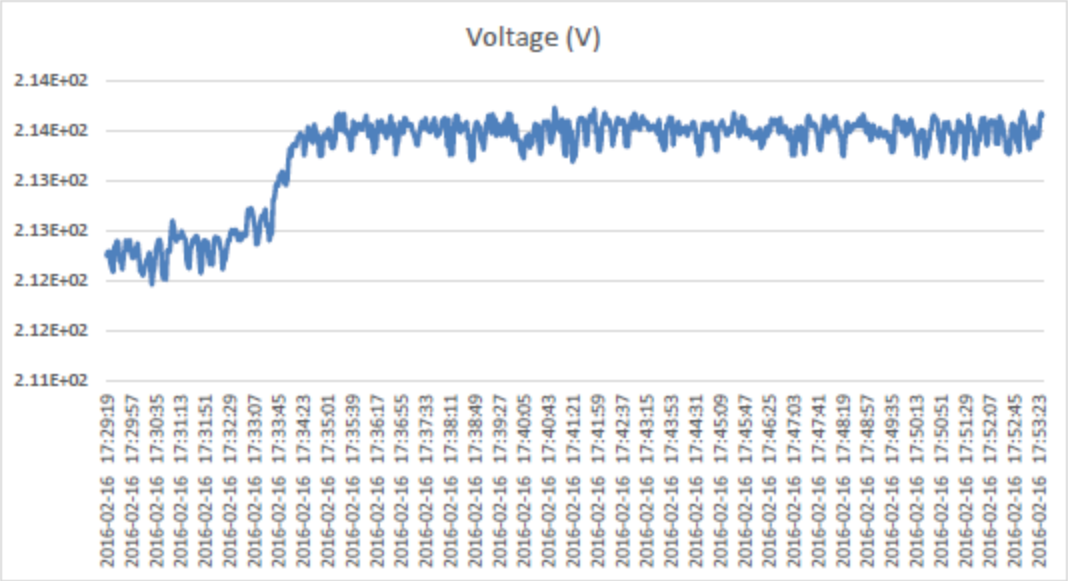


Figure 9: Grid Voltage Profile for Second Experiment

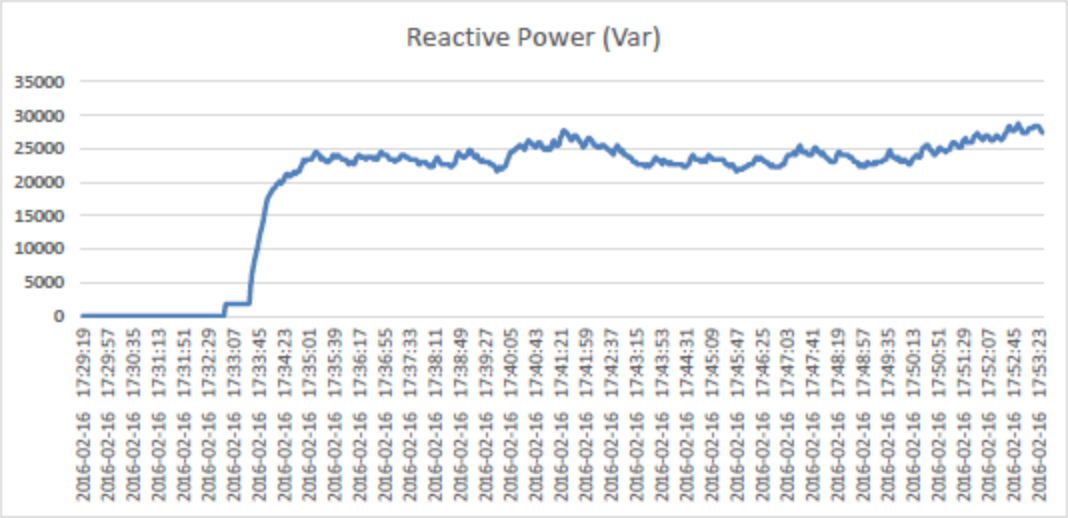


Figure 10: GTI Reactive Power for Second Experiment

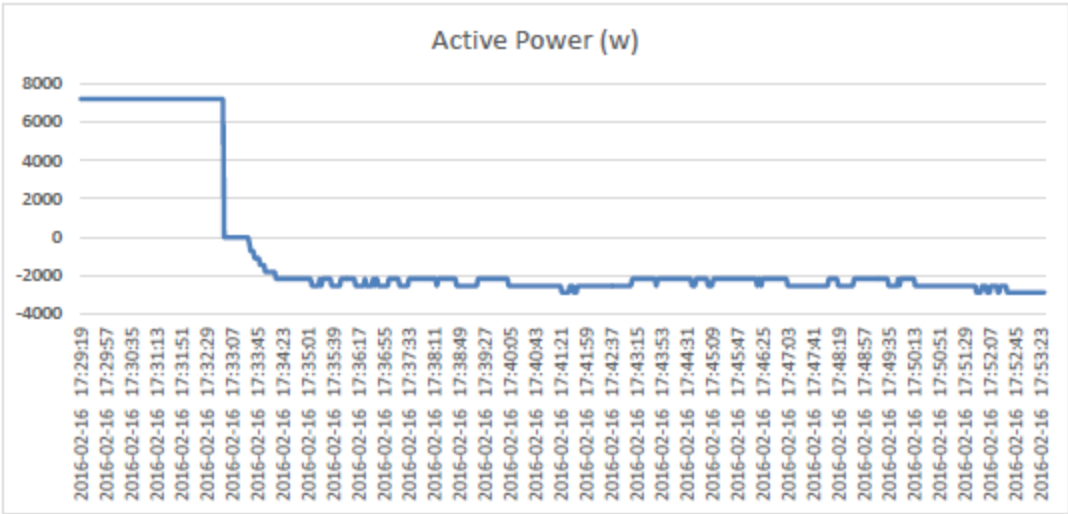


Figure 11: GTI Active Power for Second Experiment

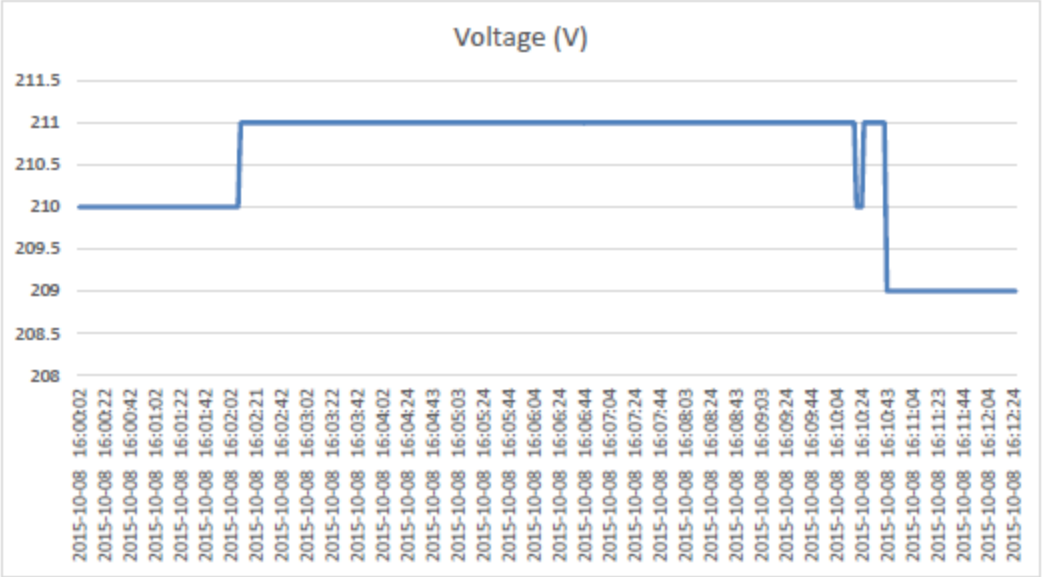


Figure 12: Grid Voltage Profile for Third Experiment

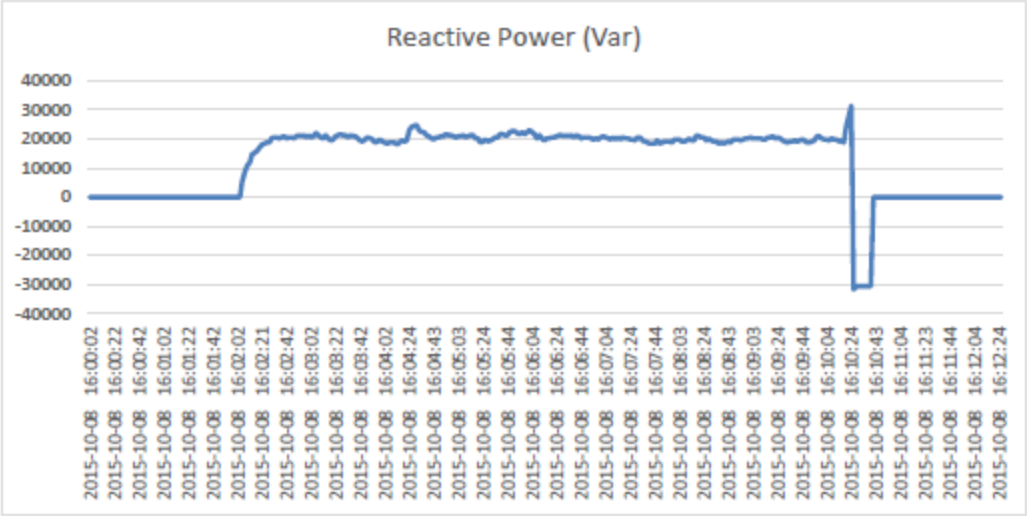


Figure 13: GTI Reactive Power for Third Experiment

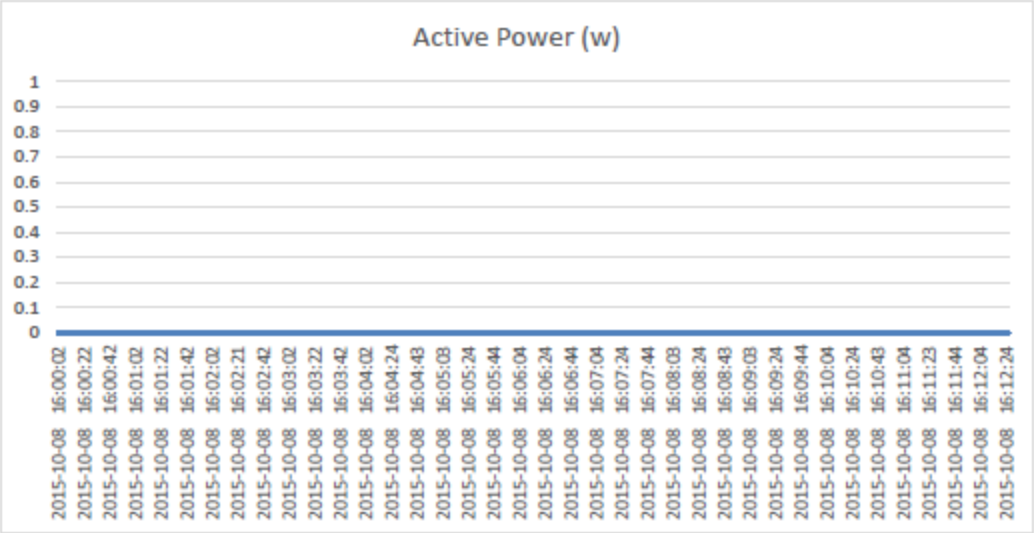


Figure 14: GTI Active Power for Third Experiment

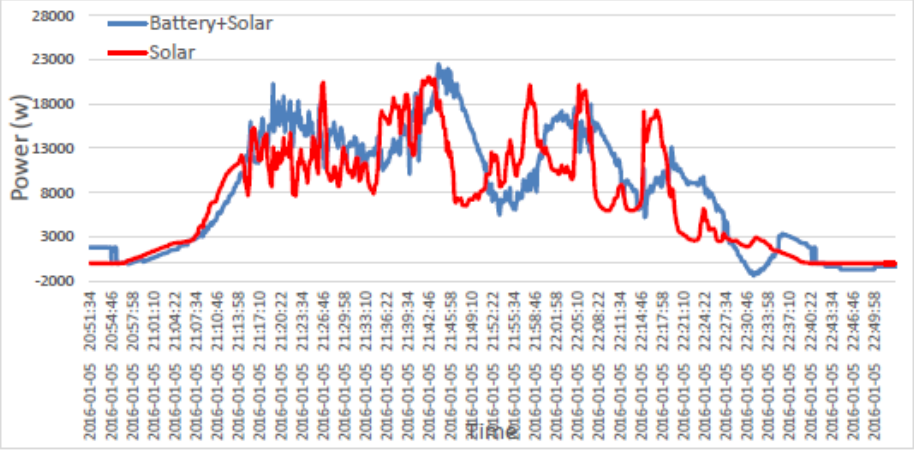


Figure 15: Output Power of Solar and Battery

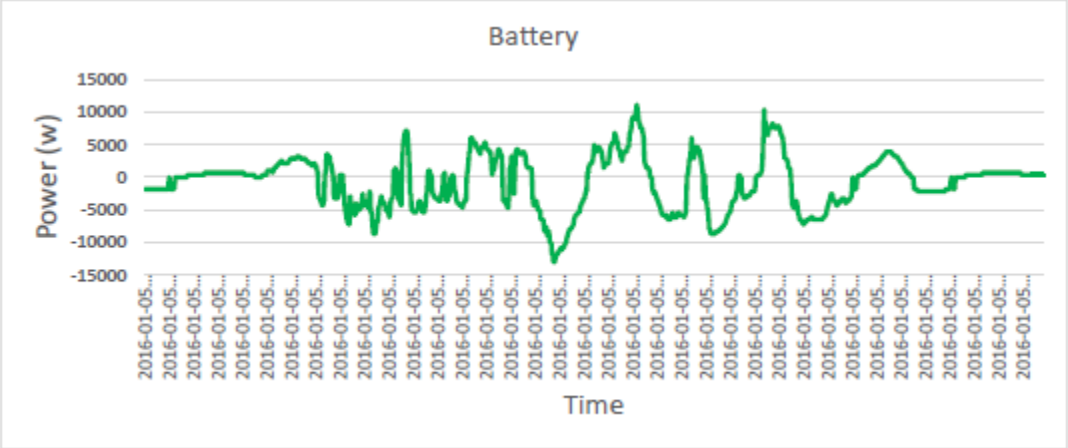


Figure 16: Battery Reaction to Command Sent by Control Center

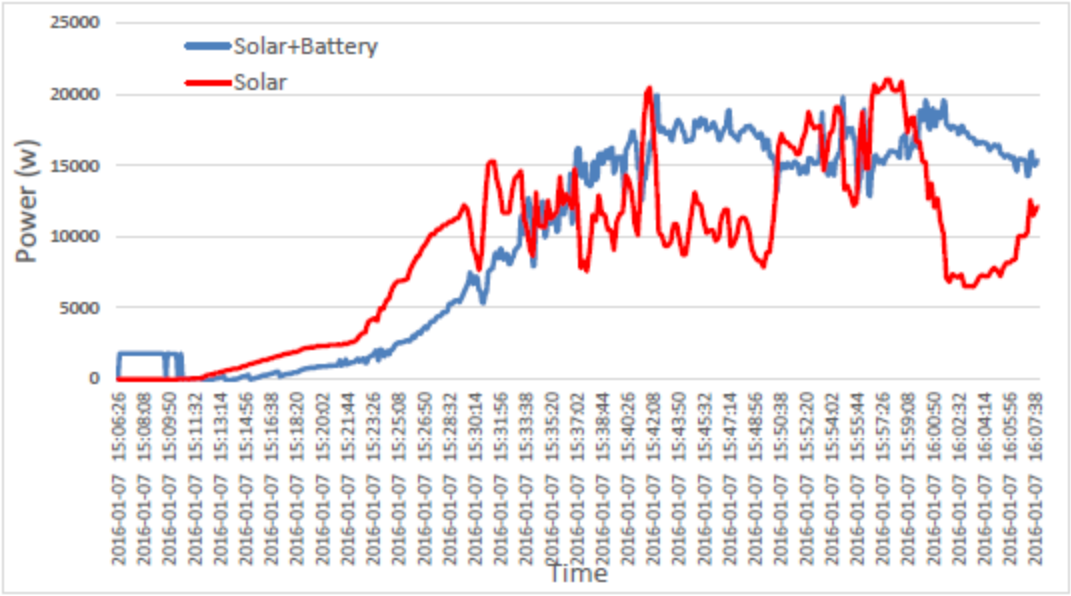


Figure 17: Output Power of Solar and Battery Employing New Method

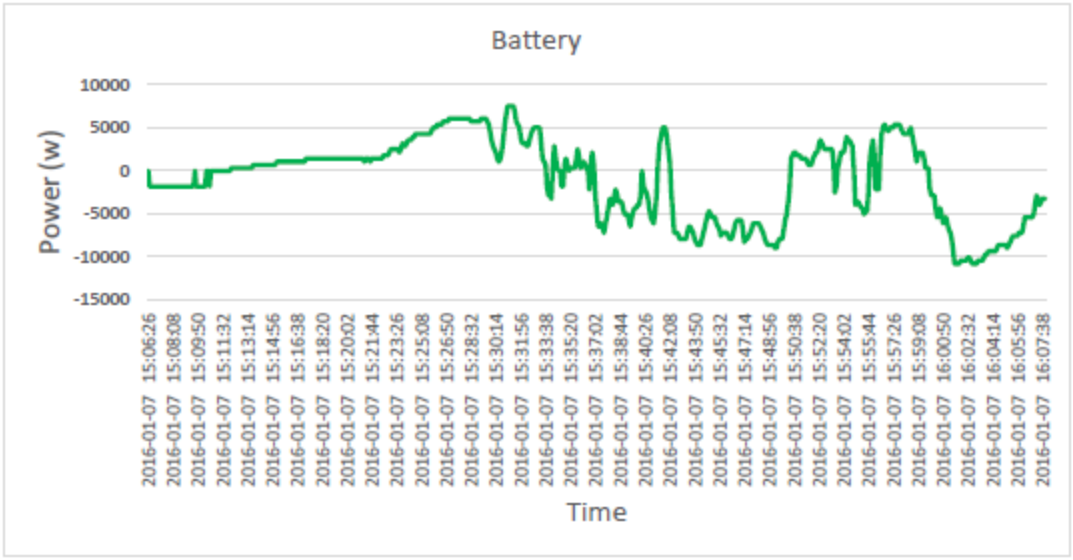


Figure 18: Battery Reaction

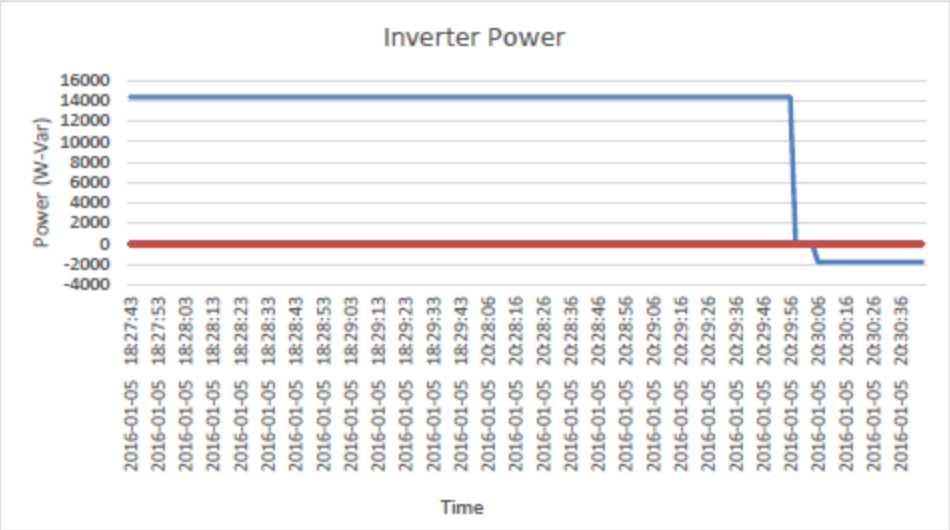


Figure 19: Inverter Active Power (Blue) and Reactive Power (Red)

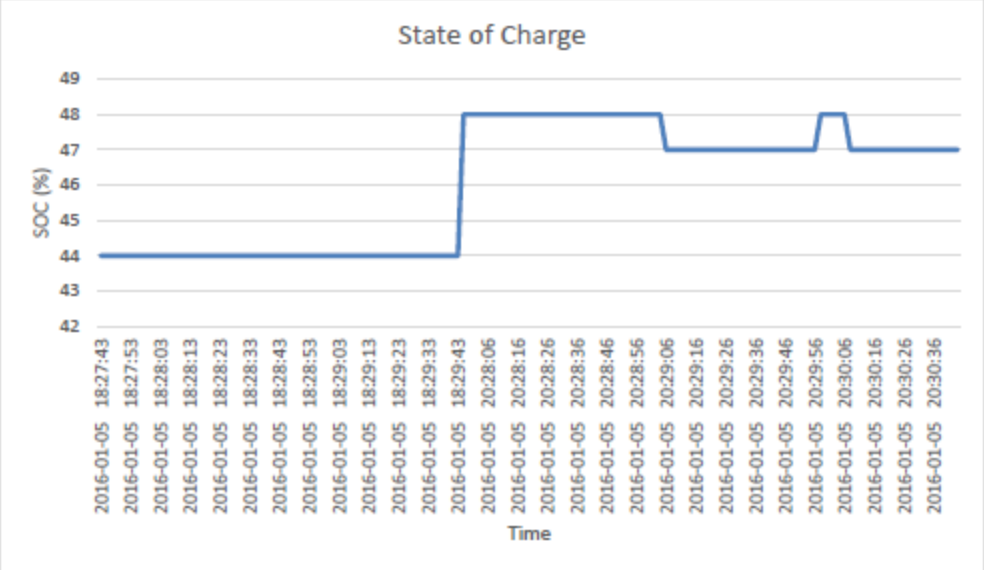


Figure 20: State of Charge of Battery

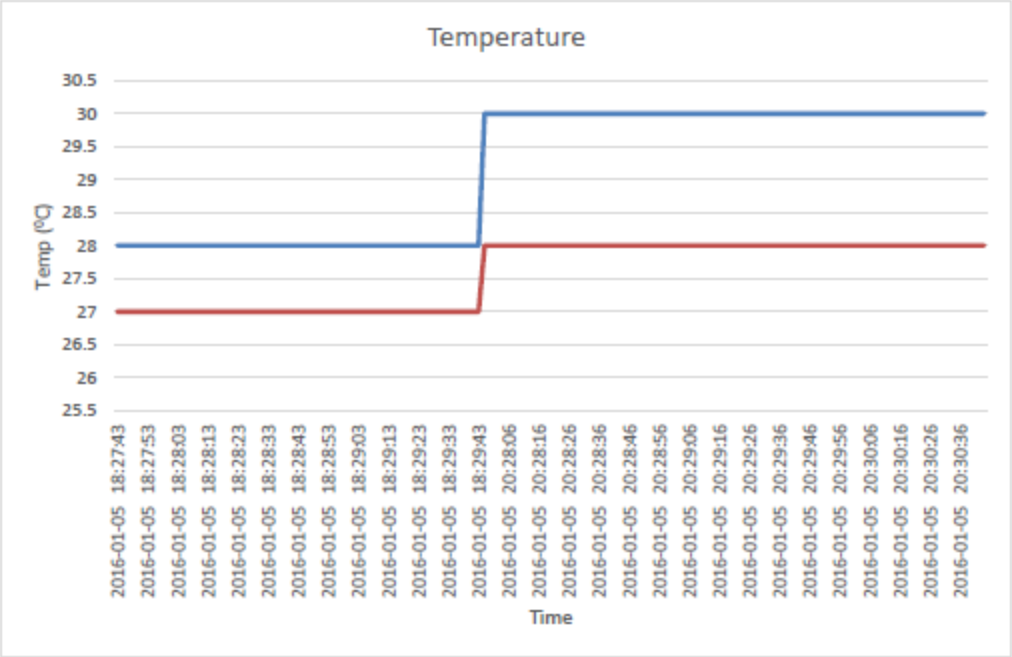


Figure 21: Minimum (Red) and Maximum (Blue) of Cells' Temperature

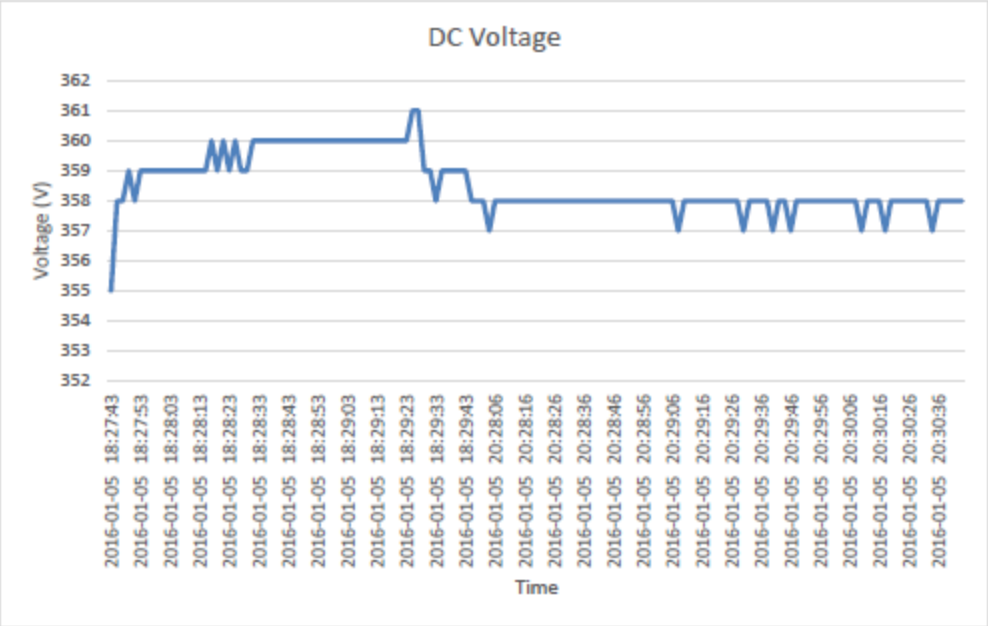


Figure 22: DC Voltage of the Battery

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Appendix AJ UCLA TPR EV Use Case 16

Technology Performance Report (TPR)
Use Case (Demonstration) #16
June 25, 2016

Demo/Use Case Name: Aggregation of Batteries

Brief Description:

The purpose of this use case was to explore the feasibility of load-shedding using a group of EV chargers. Various aggregation scenarios were tested in the demonstration.

Design Document Methodology

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. By sending demand response signals to the EV Control Center through the Super Control Center, the UCLA EV team was able monitor and collect data during a load-shedding event.

Demo responsibilities

This demonstration was designed to explore the feasibility of load-shedding using a group of EV chargers. Various aggregation scenarios were tested in this demonstration. The success criteria for this demonstration included a detailed outcome report describing the optimal aggregation, control methods and potential benefit analysis. The demonstration was executed on the UCLA campus.

Demo steps and flow

1. Charging Stations records EV Vitals
2. Charging Stations records Scenario Data
3. EV Vitals & Scenario Data sent to Control Center
4. Control Center sends commands to Charging Stations
5. Charging Stations charges EV per commands
6. On periodic basis, Charging Stations will report to Control Center status and accumulative charging data
7. EVs inform Stations charging is complete
8. Charging Stations reports results of charge to Control Center
9. Charging Stations inform operator results of charging session
10. EV Operator removes & stores Charging Cable
11. Charging Stations resets for new charging session

Planned approach

34. Perform load-shedding event via the Super Control Center
35. Monitor and evaluate data from the event
36. Document and report on the feasibility of load-shedding using EVs and EV chargers

Final Used Methodology

Key changes in Demo design and justification

The original Use Case design was focus on the operation of individual EV charging station and data collection. Based on UCLA SMERC Team's research result and development effort, in order to achieve monitoring and controlling of groups of aggregated EV chargers, a flexible platform with hierarchical infrastructure was required. Therefore, the demonstration steps were changed to the following:

1. A demand response event is manually triggered through SCC i nterface
2. The SCC operator chooses the parking structure to shed EV charging load.
3. Load Shedding command is sent to EV control Center
4. EV Control Center determines how much load can be reduced based on current EV charging load.
5. EV Control Center sends commands to Charging Stations
6. On periodic basis, Charging Stations will report to Control Center status and accumulative charging data
7. Aggregated EV charging information is sent to SCC.
8. SCC operator observe load shedding on SCC
9. Demand response event is completed.
10. SCC sends command to EV control center to end load shedding event.
11. EV control center sends command to each individual charger to resume original charging power
12. SCC operator observes EV charging load return to normal.

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- 137 EV Chargers
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- To conduct the work activities outlined under the "**Key changes in Demo design and justification**"
- Successfully demonstrate load shedding and produce an outcome report describing the optimal aggregation, control methods, and potential benefit analysis.

Progress vs. success criteria

1. A demand response event is manually triggered through SCC i nterface -

Complete

2. The SCC operator chooses the parking structure to shed EV charging load - **Complete**
3. Load Shedding command is sent to EV control Center - **Complete**
4. EV Control Center determines how much load can be reduced based on current EV charging load - **Complete**
5. EV Control Center sends commands to Charging Stations - **Complete**
6. On periodic basis, Charging Stations will report to Control Center status and accumulative charging data - **Complete**
7. Aggregated EV charging information is sent to SCC - **Complete**
8. SCC operator observe load shedding on SCC - **Complete**
9. Demand response event is completed - **Complete**
10. SCC sends command to EV control center to end load shedding event - **Complete**
11. EV control center sends command to each individual charger to resume original charging power - **Complete**
12. SCC operator observes EV charging load return to normal – **Complete**
13. Demonstrate load shedding and produce an outcome report describing the optimal aggregation, control methods, and potential benefit analysis – **Complete**

Observations and Results

Observations and Results

From the data collected, UCLA SMERC Team achieved the goal of this Use Case and successfully performed various aggregated load shedding event.

The advantages of such system included:

- Modular and open design for ease of integration with various type of end devices.
- Provide multiple layers of authentication and privileges to manage groups of EV charging stations.
- While SCC focus on higher level energy management, EV control center can manage complex scheduling algorithm to control individual charging plug.

Lessons Learned

- Infrastructure requires a reliable communication network. If the communication network is not proficient or has limited bandwidth, problems may occur.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected large amount of data has been collected associated with this Use Case. The data includes an aggregate of active power usage of all EV charging stations at each of UCLA's parking structure for five months, from October 2015 to February 2016.

Data Collection Summary

Location	Voltage	Connector type	Plug Points	Max Power (kW)
PS 9 Level 4	120 V	NEMA 5-15	4	1.8
PS 9 Level 6	120 V	NEMA 5-15	4	1.8
PS 8 level 2 South	208 V	J1772	4	6.6
PS 8 level 2 North	208 V	J1772	4	6.6
PS 2 level 2	120 V	NEMA 5-15	4	1.8
PS 3 level 4	120 V	NEMA 5-15	4	1.8
PS 3 level 2	208V	J1772	4	6.6
PS 4 Box 1	208 V	J1772	4	6.6
PS 4 Box 2	208 V	J1772	4	4.2
PS 2	208 V	J1772	4	6.6
DCFC PS 4	480 V	CHAdeMO	1	50
Total			41	94.4

Table 1: Participating Charging Stations

Load Shedding Level	Super Control Center	EV Control Center
Microgrid level	X	
Organization level		X
Parking Structure level	X	X
Charging Box level		X
Individual plug point level		X

Table 2: Load Shedding Levels Between SCC and EVCC

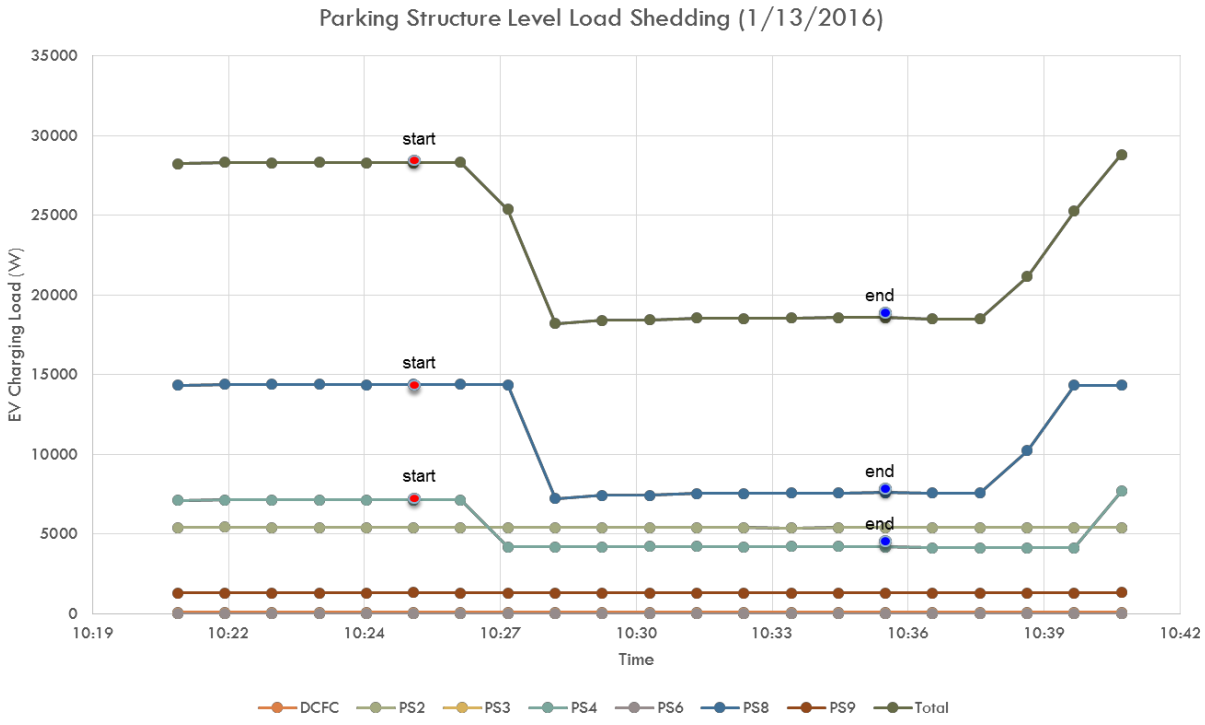
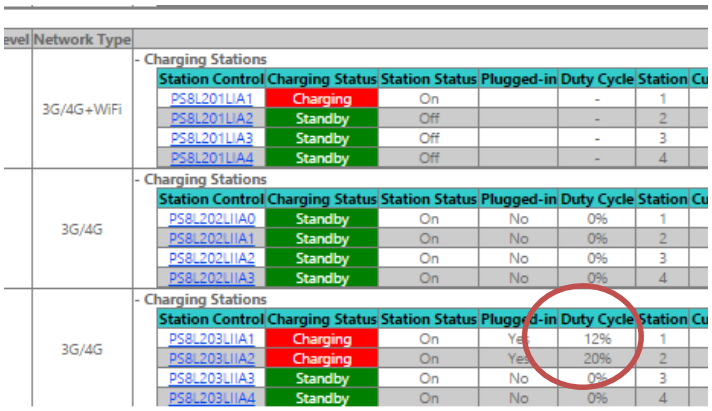


Figure 1: Parking Structure Level Load Shedding



evel	Network Type							
		- Charging Stations						
	3G/4G+WiFi	Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Cu
		PS8L201LIA1	Charging	On		-	1	
		PS8L201LIA2	Standby	Off		-	2	
		PS8L201LIA3	Standby	Off		-	3	
		PS8L201LIA4	Standby	Off		-	4	
		- Charging Stations						
	3G/4G	Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Cu
		PS8L202LIIA0	Standby	On	No	0%	1	
		PS8L202LIIA1	Standby	On	No	0%	2	
		PS8L202LIIA2	Standby	On	No	0%	3	
		PS8L202LIIA3	Standby	On	No	0%	4	
		- Charging Stations						
	3G/4G	Station Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Cu
		PS8L203LIIA1	Charging	On	Yes	12%	1	
		PS8L203LIIA2	Charging	On	Yes	20%	2	
		PS8L203LIIA3	Standby	On	No	0%	3	
		PS8L203LIIA4	Standby	On	No	0%	4	

Figure 2: EV Box Level Load Balancing and Shedding Based on Priority Charging



Figure 3: Station records for Priority Charging

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

- By utilizing EV batteries, a utility would have the ability to prevent blackouts and/or brownouts by reducing peak demand, thereby saving money.

Realized Impacts and Benefits to Date

During a load shedding event performed by the UCLA EV team, the team was able to shed approximately 28 kW.

Appendix AK UCLA TPR EV Use Case 17

Technology Performance Report (TPR)
Use Case (Demonstration) #17
June 25, 2016

Demo/Use Case Name: Integration of EV and Solar

Brief Description:

The purpose of this use case was to research and determine the best usage of PV energy. The different options for determining the best usage were charging the battery, feeding back into grid, and charging EVs.

Design Document Methodology (anticipated in 2011)

Assumptions

The UCLA EV team utilized their WINSmartEV infrastructure that was developed at the beginning of the Smart Grid Regional Demonstration Program. Additionally, the team installed a power meter on an existing inverter of a photovoltaic array on the rooftop of one of the buildings on the UCLA campus. With this setup, the UCLA EV team demonstrated the following: PVs supplying the grid, PVs supplying EVs, PVs supplying energy storage batteries, and integrating PVs, EVs, and energy storage batteries.

Demo responsibilities

In this demonstration, the EV project team installed solar panels as a distributed energy source. The solar panels were installed with an energy management system that communicated back to the SG EV Control Center to determine how to use the energy collected by the solar panel. The collected energy could be stored in the external battery system installed (P2B), supplied to power loads, fed into the grid (P2G), or used to charge EVs connected to charging stations (P2V). Various loading scenarios were demonstrated to monitor the energy usage and grid impacts. This demonstration was conducted at the SG Power Lab, the SG EV Control Center and Various Demo Sites.

Demo steps and flow

A. PV to Grid
   1. **Control Center send signal to connect PV to Grid**
   2. **Periodically, Control Center collects PV Vitals**
   3. **PV stops generating energy**
   4. Control Center accumulates and archives PV Vitals data

B. PV to Battery
   1. **Control Center send signal to connect PV to CES**
   2. **CES receives signal from Control Center to charge**
   3. **CES records CES vitals**

4. **CES vitals sent to Control Center**
5. **On periodic basis, CES & PV report to Control Center status and accumulative charging data**
6. **CES informs Control Center charging is complete**
7. **Control Center sends signal to connect PV to Grid**
8. **CES reports results of charge to Control Center**

C. PV to EV

1. **Charging Station records EV Vitals**
2. **Charging Station records Scenario Data**
3. **EV Vitals & Scenario Data sent to Control Center**
4. **Control Center send signal to connect PV to Charging Station**
5. **PV collects & sends Vitals to Control Center**
6. **Control Center sends commands to Charging Station (to charge using PV energy)**
7. **On periodic basis, PV will report to Control Center status and accumulative energy data**
8. **On periodic basis, EV will report to Control Center status and accumulative charging data**
9. **EV informs Control Center charging is complete**
10. **Control Center sends signal to connect PV to Grid.**
11. **PV reports results to Control Center**
12. EV reports results of charge to Control Center

Planned approach

37. Install PV array system
38. Demonstrate scenarios
39. Monitor and evaluate data from EV chargers, PV array, and battery energy storage system
40. Document and report on the integration of EVs and solar.

Final Used Methodology

Key changes in Demo design and justification

There were no new changes to the demonstration design.

Technologies Deployed

List of systems/equipment deployment

- Super Control Center
- EV Control Center
- PV Array
- 136 EV Chargers
- Battery Energy Storage System
- Electric Vehicles

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification"**

Progress vs. success criteria

A. PV to Grid

1. **Control Center send signal to connect PV to Grid – Complete**
2. **Periodically, Control Center collects PV Vitals – Complete**
3. **PV stops generating energy – Complete**
4. Control Center accumulates and archives PV Vitals data – **Complete**

B. PV to Battery

1. **Control Center send signal to connect PV to CES – Complete**
2. **CES receives signal from Control Center to charge – Complete**
3. **CES records CES vitals – Complete**
4. **CES vitals sent to Control Center – Complete**
5. **On periodic basis, CES & PV report to Control Center status and accumulative charging data – Complete**
6. **CES informs Control Center charging is complete – Complete**
7. **Control Center sends signal to connect PV to Grid – Complete**
8. **CES reports results of charge to Control Center – Complete**

C. PV to EV

1. **Charging Station records EV Vitals – Complete**
2. **Charging Station records Scenario Data – Complete**
3. **EV Vitals & Scenario Data sent to Control Center – Complete**
4. **Control Center send signal to connect PV to Charging Station – Complete**
5. **PV collects & sends Vitals to Control Center – Complete**
6. **Control Center sends commands to Charging Station (to charge using PV energy) – Complete**
7. **On periodic basis, PV will report to Control Center status and accumulative energy data – Complete**
8. **On periodic basis, EV will report to Control Center status and accumulative charging data – Complete**
9. **EV informs Control Center charging is complete – Complete**
10. **Control Center sends signal to connect PV to Grid – Complete**
11. **PV reports results to Control Center – Complete**
12. EV reports results of charge to Control Center – **Complete**

Observations and Results

Observations and Results

The system was versatile in terms of structure so it was easy for additional resources to join in and show related information. As the main function of the system, the SCC could implement a wide array of scheduling algorithms. The scheduling algorithm could be defined by user and would take care of the macroscopic scale of the energy management as the role of utility manager while leaving the microscopic management role to local EV control centers. This configuration could allow a flexible structure for further scaling up. The UCLA EV team tested the scalability with Virtual Devices. The team also discussed the reliability of the Control Center as it was a potential concern for actual implementation in industry.

Lessons Learned

- Equipment used will need its own interface for an upper-level EMS system.
- Due to delays in the construction of a photovoltaic array system, UCLA had to utilize an existing PV array.

Best Practices

None established.

Results of Data Collection

- The UCLA EV team collected numerous data points from 136 Level 1 and Level 2 EV chargers for 5 months. These data points include the timestamp and the active power of all stations in each of UCLA's Parking Structures, PV generation, and battery operation.

Data Collection Summary

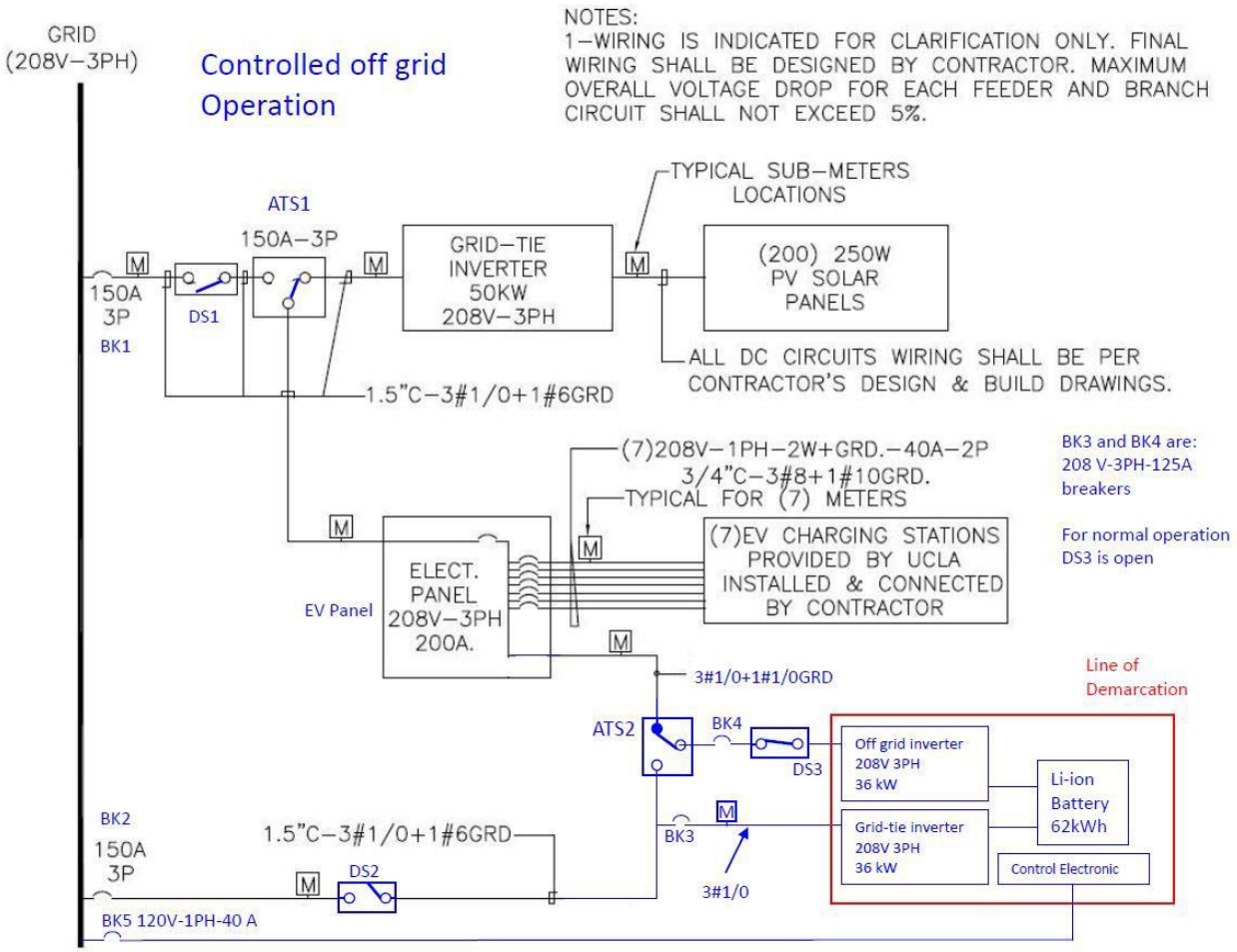


Figure 1: PV, EV, and Battery System Single Line Diagram

Location	Voltage	Connector type	Plug Points	Max Power (kW)
PS 9 Level 4	120 V	NEMA 5-15	4	1.8
PS 9 Level 6	120 V	NEMA 5-15	4	1.8
PS 8 level 2 South	208 V	J1772	4	6.6
PS 8 level 2 North	208 V	J1772	4	6.6
PS 2 level 2	120 V	NEMA 5-15	4	1.8
PS 3 level 4	120 V	NEMA 5-15	4	1.8
PS 3 level 2	208V	J1772	4	6.6
PS 4 Box 1	208 V	J1772	4	6.6
PS 4 Box 2	208 V	J1772	4	4.2
PS 2	208 V	J1772	4	6.6
DCFC PS 4	480 V	CHAdeMO	1	50
Total			41	94.4

Table 1: Participating Charging Stations

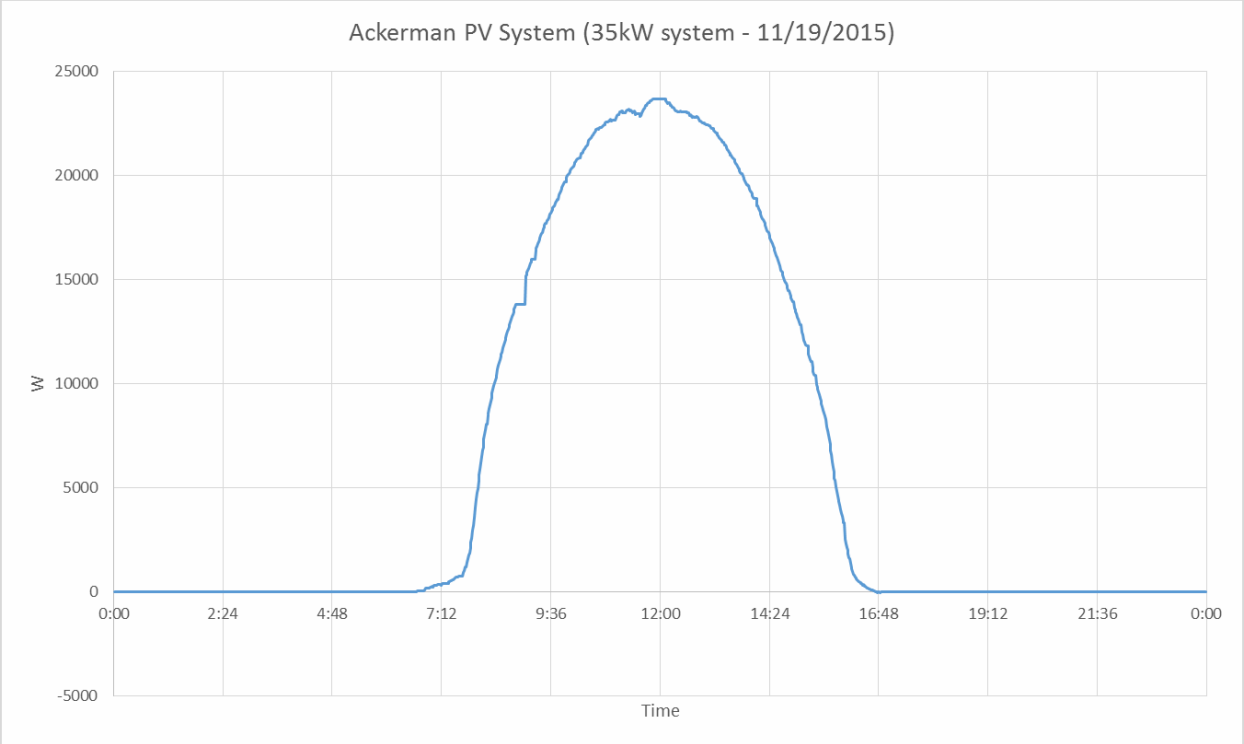


Figure 2: Ackerman PV System Nov 19 2015

Month	PV Generation (kWh)

10/2015	4.865
11/2015	4.264
12/2015	3.572
01/2016	3.133
02/2016	4.899
Total	20.733

Table 2: PV Power Generation Summary

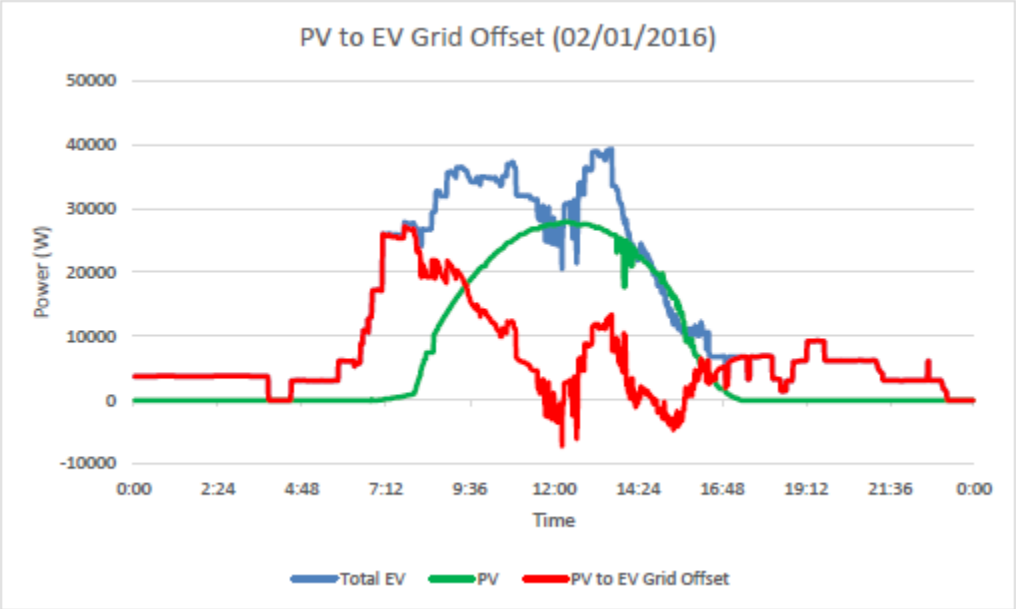


Figure 3: Aggregated PV Power Generation in UCLA on Feb 01 2016

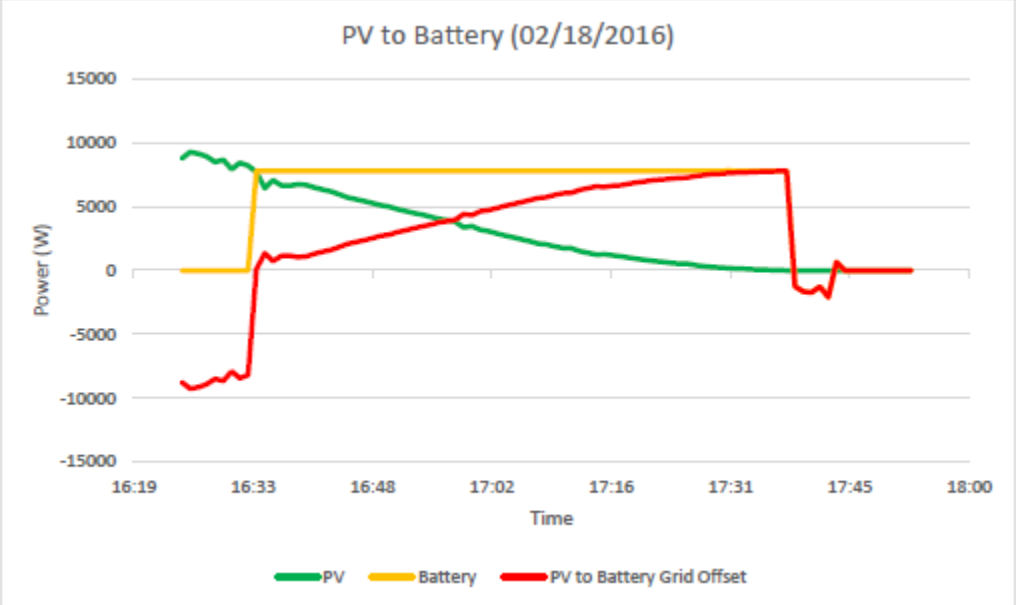


Figure 4: Battery Operation in PV to Battery Experiment on Feb 18 2016

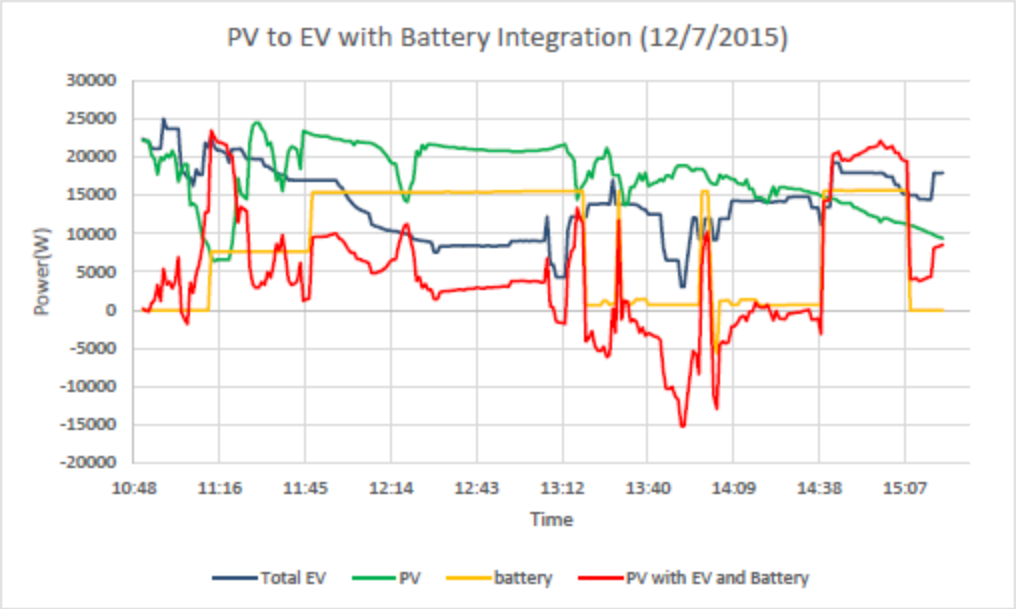


Figure 5: Battery Operation within PV to Grid with EV and Battery Experiment on Dec 7 2015

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Appendix AL Use Case #14

Technology Performance Report (TPR)
Use Case (Demonstration) #14
August 25, 2016

Demo/Use Case Name: Garage of the Future

Brief Description:

This use case presented different methods of EV (Electric Vehicle) charging. Options include: charge from battery, charge from grid, and charge from renewable resources such as wind and solar.

Design Document Methodology

Assumptions

For this use case, different modes of operation at the Garage of the Future (GoF) were demonstrated. The combination of Grid, Photovoltaic (PV), and a battery system provided different modes of EV charging. In addition to charging, the discharging of EV was also demonstrated by feeding back to the grid. Assumptions were made to provide the best scenario which can demonstrate the most variations in half-automated but repetitive operations.

Demo responsibilities

The Garage of the Future demonstration will present different methods of EV charging. Charging EVs through the use of solar and wind resources will be demonstrated. In addition to using renewables for charging EVs (P2V), charging from a local energy source (B2V) will also be demonstrated. The Garage of the Future will be located in the Main Street facility.

The success criteria for this demo will be the definite evaluation of feasibility for different methods of EV charging.

Demo steps and flow

Grid to EV

1. Run **Use Case #7** for more than 1 month to collect enough data to analyze and report results
2. Review power consumption and EV data by time series (report each month)
3. Review any anomalies (Charging Stations or BMS errors) and report

Battery to EV

1. Run **Use Case #8b** for more than 1 month to collect enough data to analyze and report results
2. Review power consumption and EV data by time series (report each month)
3. Review any anomalies (Charging Stations or BMS errors) and report

PV to Battery / PV to EV

1. Run **Use Case #17** for more than 1 month to collect enough data to analyze and report results
2. Review power consumption and EV data by time series (report each month)
3. Review any anomalies (Charging Stations or BMS errors) and report

Wind to Battery / Wind to EV

1. Run **Use Case #17** (using Wind generation) for more than 1 month to collect enough data to analyze and report results
2. Review power consumption and EV data by time series (report each month)
3. Review any anomalies (Charging Stations or BMS errors) and report

Planned approach

4. Analyze collected data and store for later usage.
5. Demonstrate the operation of EV charging/discharging by different resources: charging from batteries, PV, or the grid.
6. Finalize the demonstration report.

Final Used Methodology

Key changes in Demo design and justification

Due to certain limitations to the Garage of the Future, several key changes in the demonstration design occurred:

Grid to EV:

Because Use Case 7 was not demonstrated at the Garage of the Future, the data obtained were not related to the GoF, power consumptions were not available, and the EV data was not applicable for this use case. To cover the requirements, the planned data set was replaced with a 1 month data collection in G2V mode with availability of anomalies through SIS system logs.

Battery to EV:

Data was collected from the USC EV team and only through simulations. To cover the gap, a B2V daily scenario was designed and performed for 1 month to provide the required data.

PV2Battery, PV to EV:

In addition to the 1 month collected data from Use Case 17 and to better align with the requirements from Use Case 7 and Use Case 8b, a dedicated scenario for similar operation of the GoF was integrated into 1 month data collection period for Use Case 14.

Wind2B, Wind2V:

Due to the unavailability of a wind turbine, this scenario was removed from data collection operations.

Due to these changes, the Demonstration steps and flow were changed to the following:

Grid to EV

1. Run G2V at the GoF for more than 1 month to collect enough data to analyze and report results
2. Review power consumption and EV data by time series (report each month)
3. Review any anomalies (Charging Stations or BMS errors) and report

Battery to EV

1. Run B2V at the GoF for more than 1 month to collect enough data to analyze and report results
2. Collect data from USC EV team on Use Case 8
3. Review power consumption and EV data by time series (report each month)
4. Review any anomalies (Charging Stations or BMS errors) and report

PV to Battery / PV to EV

1. Run Use Case #17 for more than 1 month to collect enough data to analyze and report results
2. Review power consumption and EV data by time series (report each month)
3. Review any anomalies (Charging Stations or BMS errors) and report

Technologies Deployed

List of systems/equipment deployment

- AMI Meter (Net meter)
- At least 1 EV Charger
- At least 1 EV Discharger
- Solar panels, grid-tied-inverter
- Energy storage(Battery), battery charger
- Electric Vehicle
- Various electrical sensors and metering system
- Network and data flow between GoF and control center

Success Criteria

Description of success criteria for this Demo

- To conduct the work activities outlined under the "**Key changes in Demo design and justification"**

Progress vs. success criteria

Grid to EV

1. Run G2V at the GoF for more than 1 month to collect enough data to analyze and report results – **Complete**
2. Review power consumption and EV data by time series (report each month) – **Complete**
3. Review any anomalies (Charging Stations or BMS errors) and report – **Complete**

Battery to EV

1. Run B2V at the GoF for more than 1 month to collect enough data to analyze and report results – **Complete**
2. Collect data from USC EV team on Use Case 8 – **Complete**
3. Review power consumption and EV data by time series (report each month) – **Complete**
4. Review any anomalies (Charging Stations or BMS errors) and report – **Complete**

PV to Battery / PV to EV

1. Run Use Case #17 for more than 1 month to collect enough data to analyze and report results – **Complete**
2. Review power consumption and EV data by time series (report each month) – **Complete**
3. Review any anomalies (Charging Stations or BMS errors) and report – **Complete**

Observations and Results

Observations and Results

- The designed and integrated scenario was completed, to have a daily (repetitive) charge/discharge of EV by various resources.
- With a nondestructive modification in the scenario, this use case also included EV discharging (feeding back to the grid) during the peak hours in the afternoon, and with minimum personnel requirement.
- Since using the same level 1 charger for all EV charging sessions (from Battery, grid or PV) the charge rate was equal to the 900 watt capability of the level 1 charger.

Lessons Learned

- Infrastructure requires a reliable communication network. If the communication network is not proficient or has limited bandwidth, problems may occur.
- SIS unit was not capable of remotely avoiding PV energy usage or Grid connection. To overcome this limitation, the DWP EV team used a manual disconnection of grid connectivity and PV connectivity to force the SIS unit to follow the schedule of charging/discharging the EV based on a predefined scenario.
- The solar unit was not capable of disconnecting the grid remotely, and not capable of stopping the load feed, it always fed the load from available resources acting like an uninterruptible power supply
- Additionally, the solar unit (SIS) had some limitations when it was programmed to disconnect from the grid or stop feeding the load. It should be considered for future plans and operations using this system.
- The EV internal measurements were not usually available for research purposes.
- Solar units available in the market were not capable of complete manipulation in their programs and usually had certain modes of operations and limitations on operations.

Best Practices

None established.

Results of Data Collection

Data Collection Summary

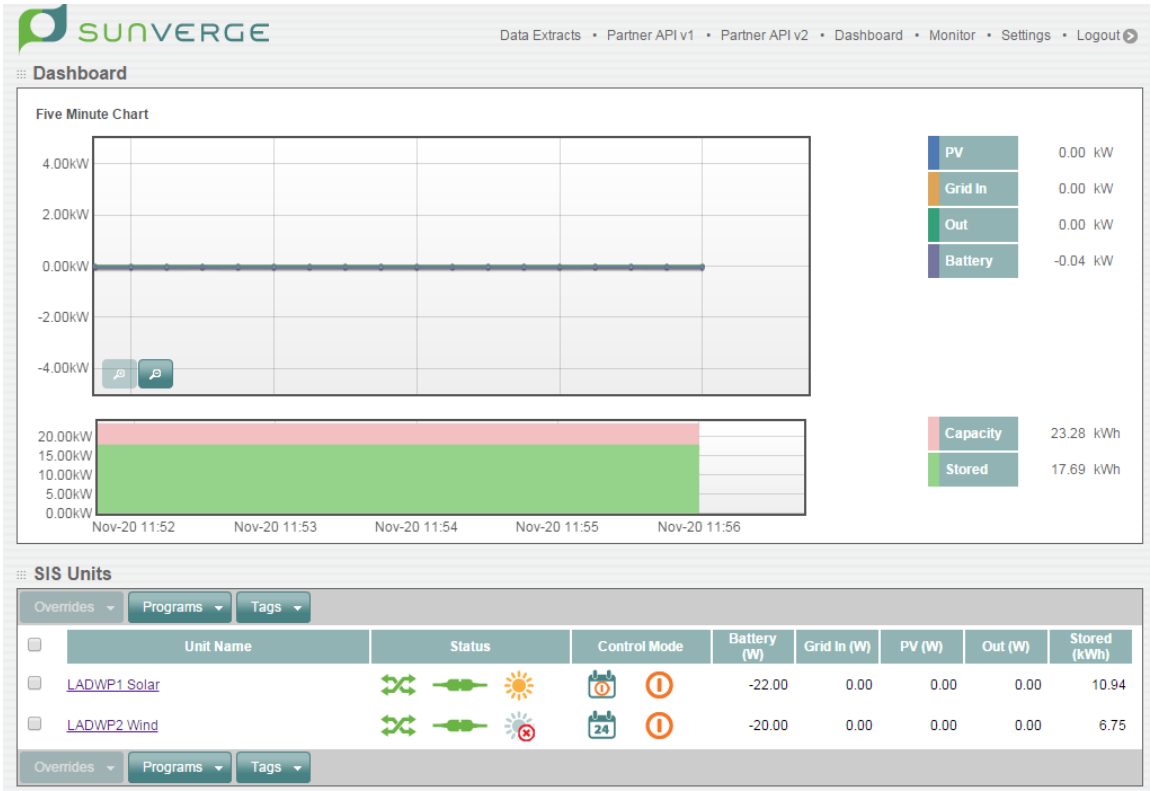


Figure 1: SIS Overall Dashboard View

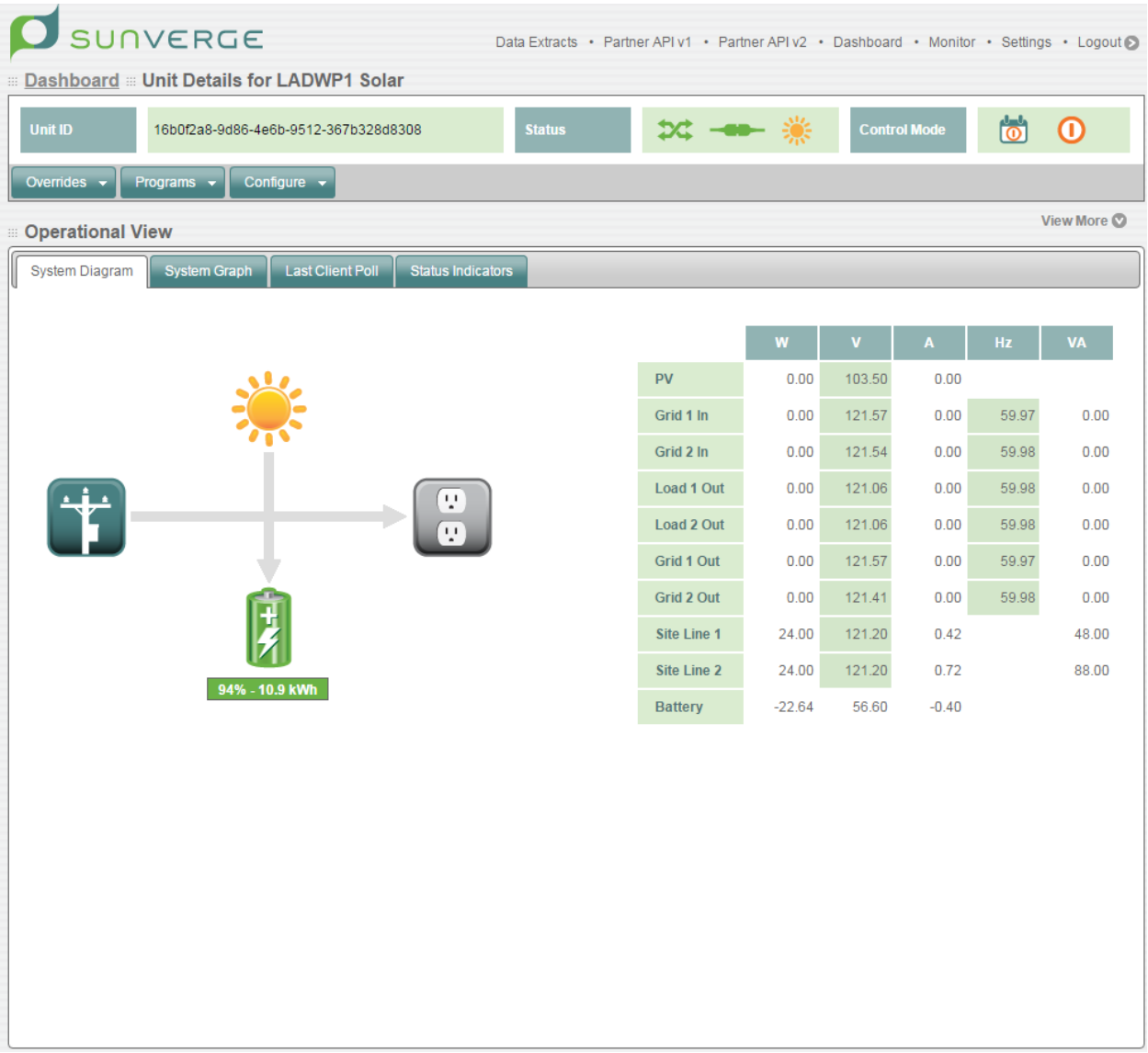


Figure 2: SIS Unit Overview Dashboard

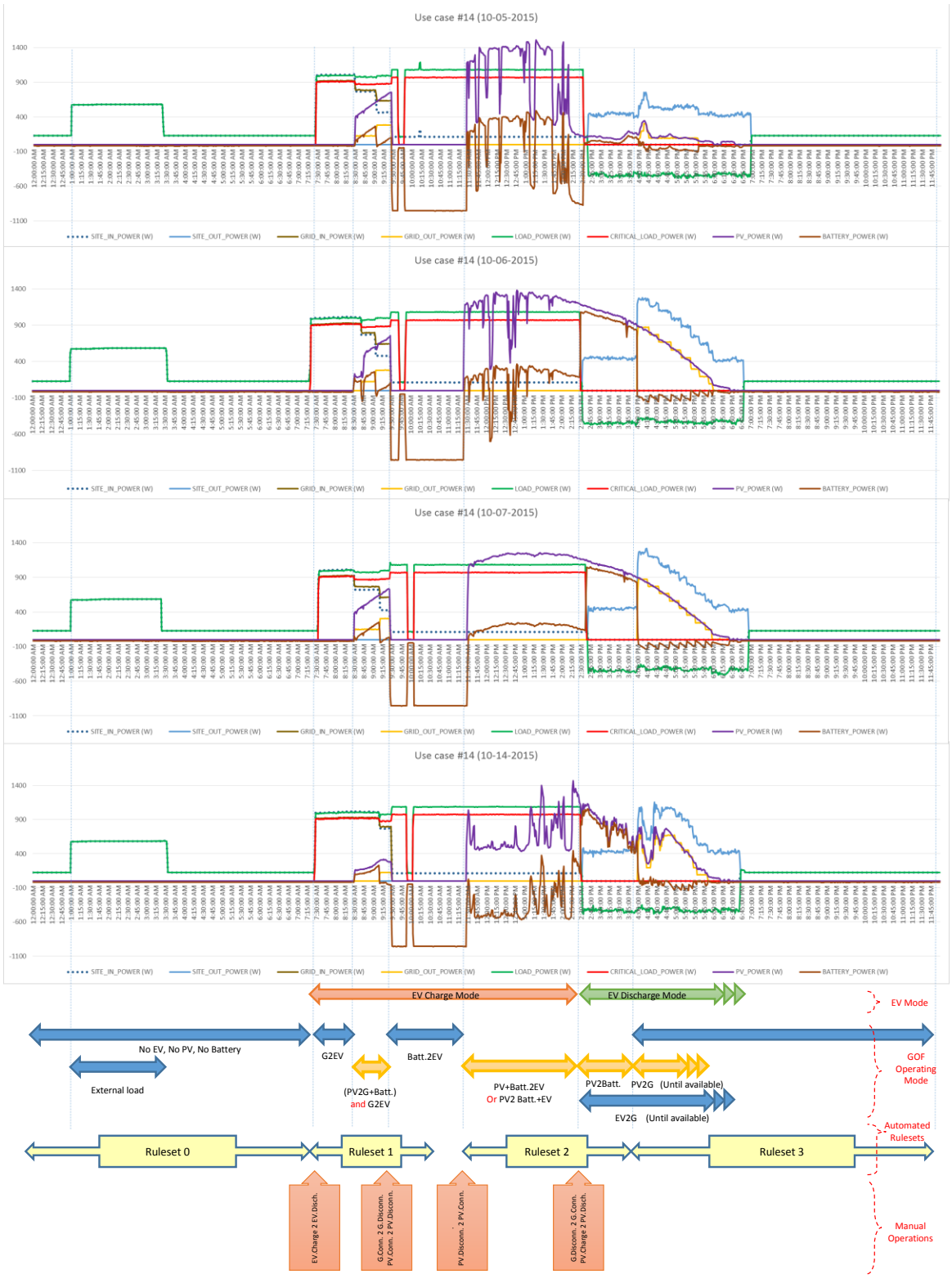


Figure 3: Data sets for October 5 2015, October 6 2015, October 7 2015, and October 14 2015

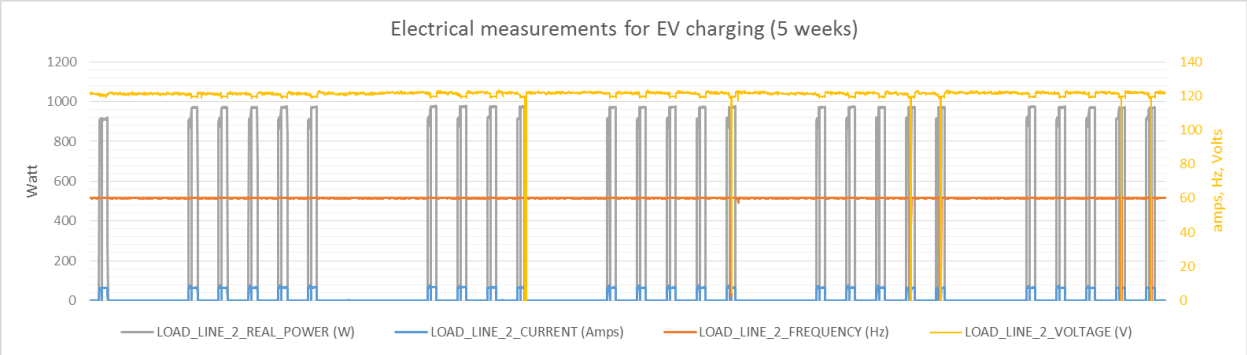


Figure 4: Electrical measurements for EV charging

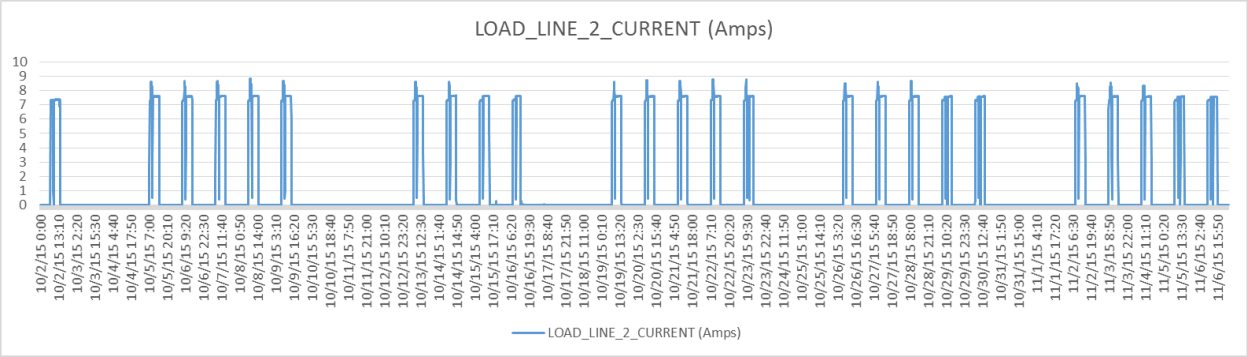


Figure 5: EV Charging Current

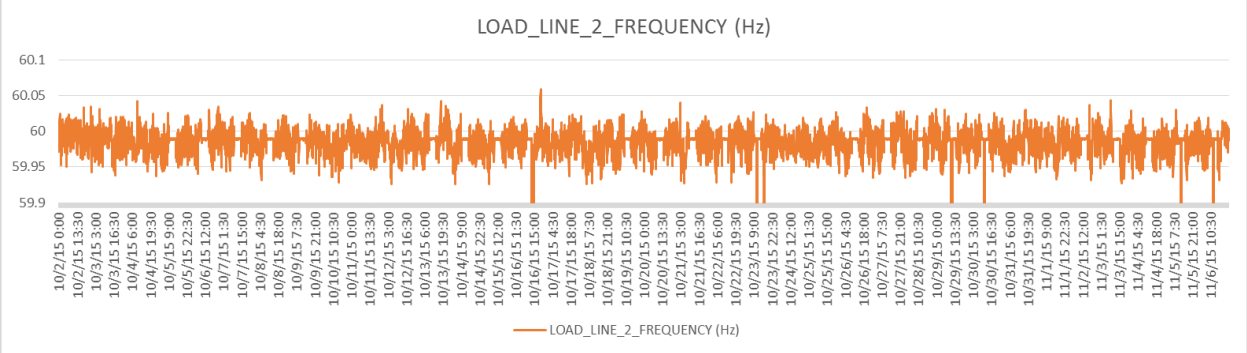


Figure 6: Frequency of Level 1 Charger

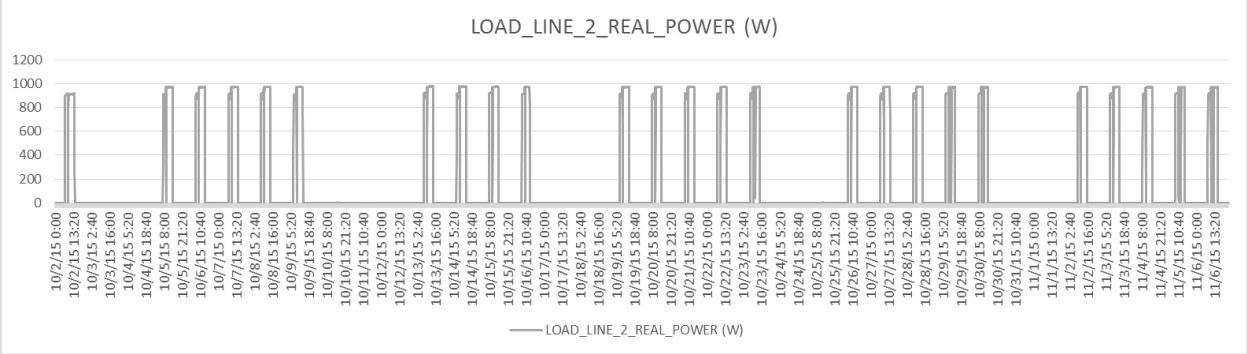


Figure 7: Active Power Flow to EV

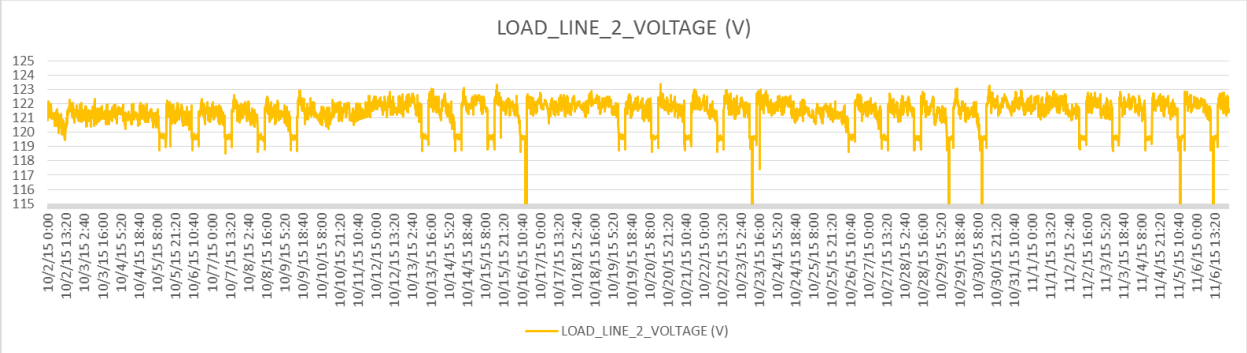


Figure 8: Line Voltage

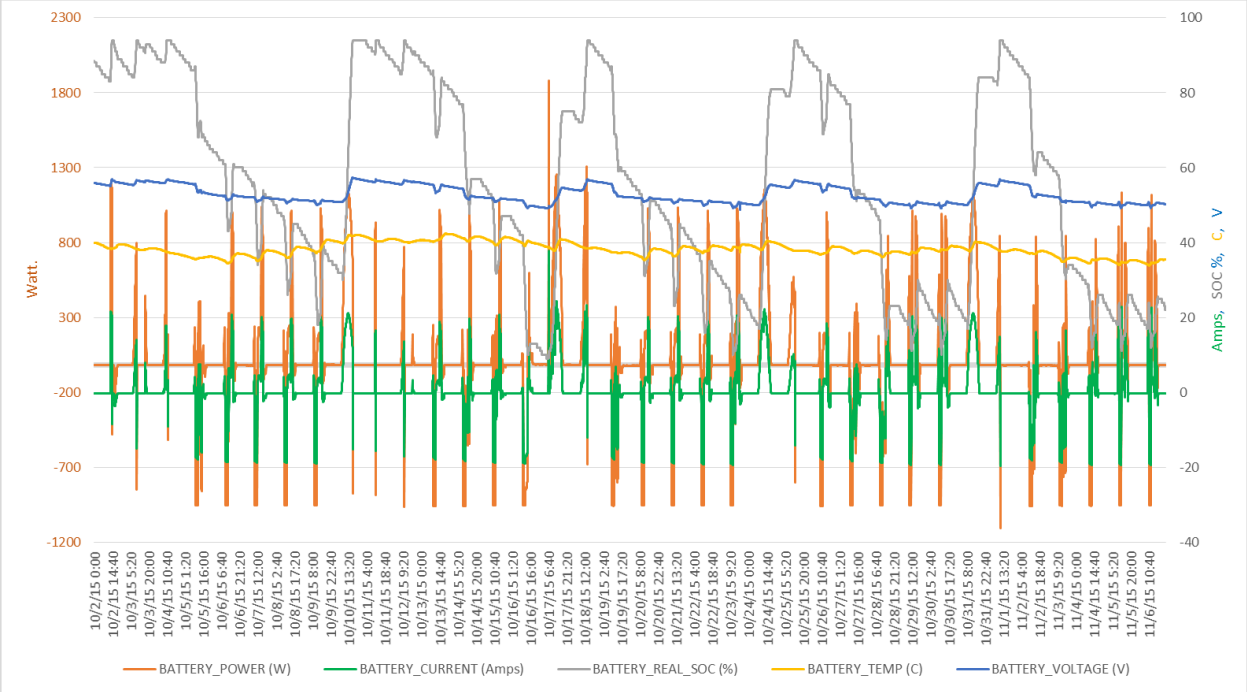


Figure 9: SIS Battery Measurements for Use Case 14

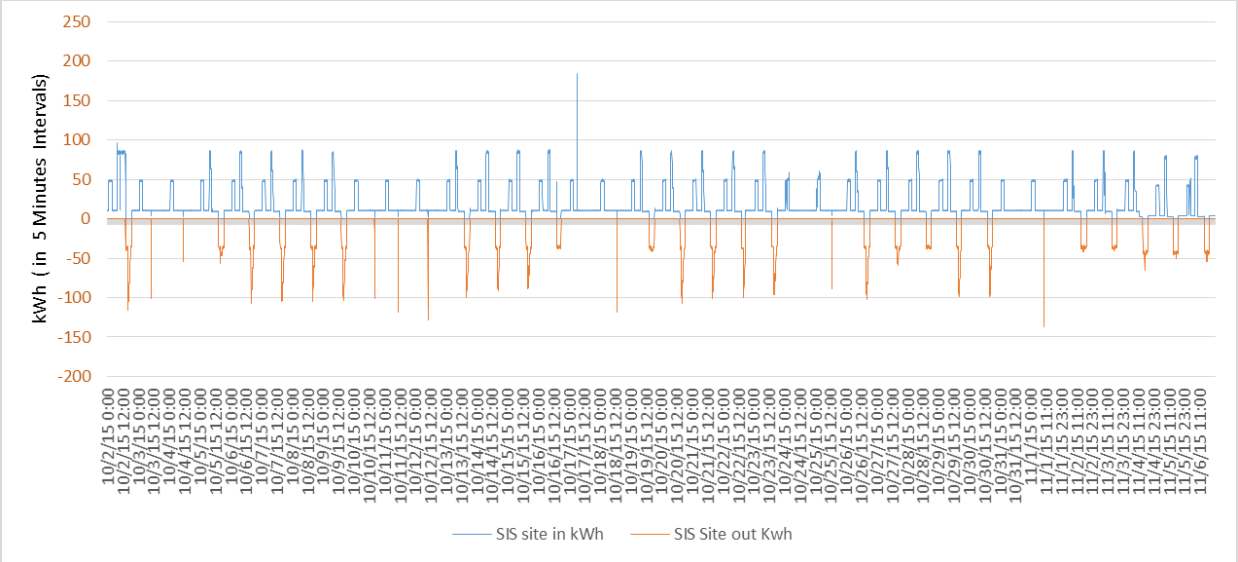


Figure 10: Site In/Out Energy Plot for the Duration of Data Collection in 5 Minute Intervals

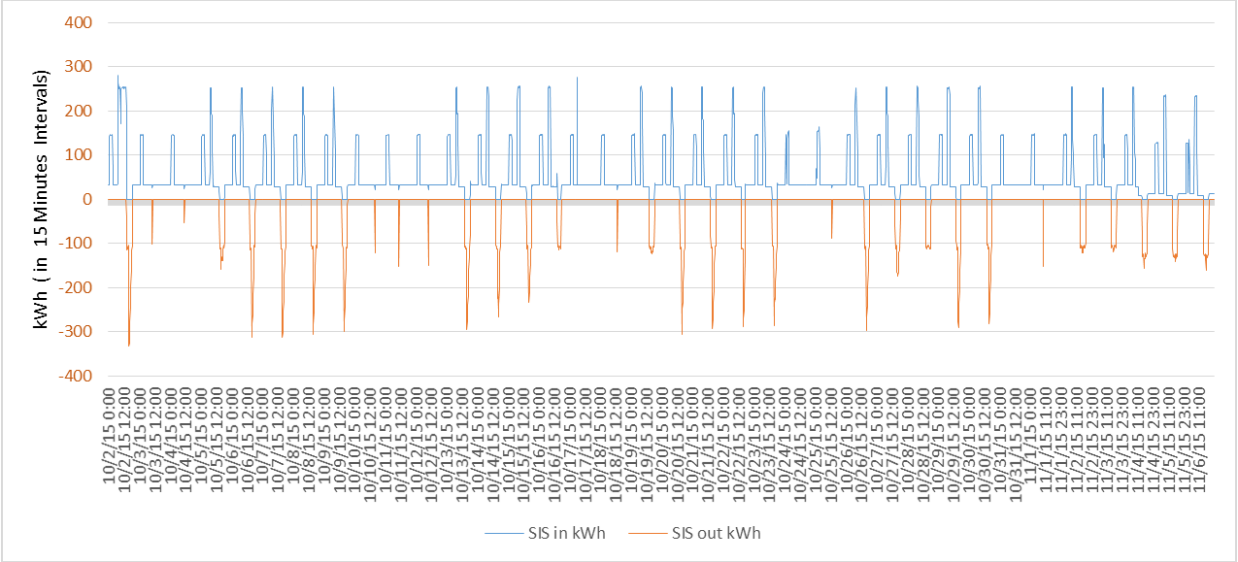


Figure 11: Site In/Out Energy Plot for the Duration of Data Collection in 15 Minute Intervals

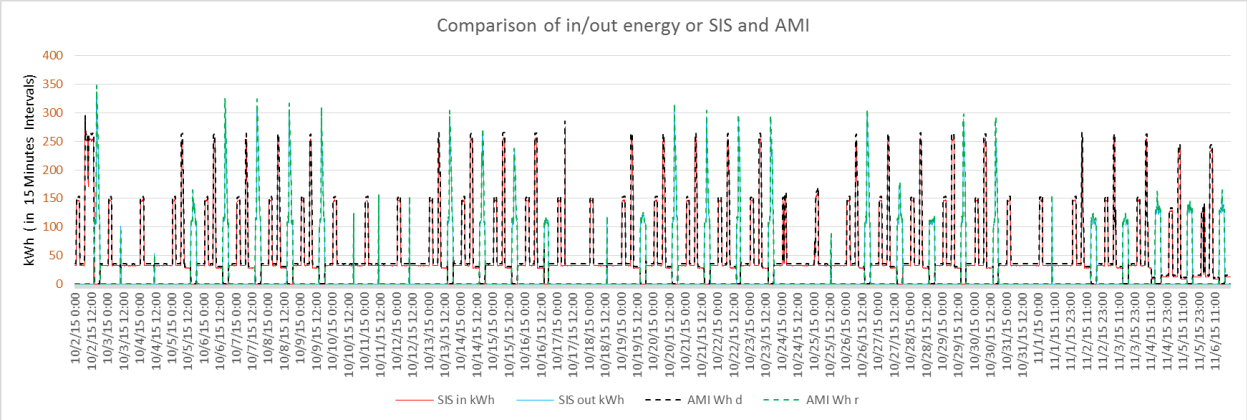


Figure 12: Comparison of AMI and Site In/Out Energy

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

The collected data could be used in overall distribution system reliability, asset management, infrastructure optimization, and cost effectiveness. The results would guide future systems development at LADWP and other utilities.

Realized Impacts and Benefits to Date

Only collected data from GoF were available to date. Various EV charging strategies were tested using available facility at GoF.

Appendix AM Use Case #15

Technology Performance Report (TPR)
Use Case (Demonstration) #15
August 25, 2016

Demo/Use Case Name: Cycling of Batteries

Brief Description:

The Cycling of the Batteries demonstration was designed for simulation of Electric Vehicle battery charging and discharging in the lab environment. The discharge methodology was implemented in a way to replicate the discharge scenario of EV driving. This demo was located in the Main Street lab facility called the Garage of the Future (GoF).

Design Document Methodology

Assumptions

Use case #15 simulated the charging and discharging of EV batteries. For this purpose, the control center needed to send signals to the battery management system to start testing the sequence. Due to limitations on controlling of EV charge and discharge remotely, based on schedule, and other limitations based on manufacturer's policies, the DWP EV team used the SIS unit battery as our scenario.

Demo responsibilities

The Cycling of the Batteries demonstration was designed for simulation of EV battery charging and discharging in the lab environment. The discharge methodology was implemented in a way to replicate the discharge scenario of EV driving. This demo was located in the Main Street lab facility.

The success criteria for Cycling of the Batteries would be the level of similarity of battery cycling to an actual discharge of EV battery under normal driving scenario.

Demo steps and flow

12. BMS records EV battery vitals data
13. Vitals data sent to Control Center
14. EV Battery cycles (charging / idle / discharging) per test scenario
15. On periodic basis, BMS will report to Control Center status and charging state data

Planned approach

41. Perform battery cycling events at Garage of the Future
42. Monitor and evaluate data from the event
43. Document and report on the cycling of the battery

Final Used Methodology

Key changes in Demo design and justification

Technologies Deployed

List of systems/equipment deployment

- AMI Meter (Net meter)
- At least 1 EV Charger (replaced due to modification of use case flow)
- Energy storage(Battery), battery charger
- Electric Vehicle (replaced due to modification of use case flow)
- Various electrical sensors and metering system
- Network and data flow between GoF and control center.

Success Criteria

Description of success criteria for this Demo

- To conduct the work activities outlined under the "**Demo steps and flow**".

Progress vs. success criteria

1. BMS records EV battery vitals data – **Complete**
2. Vitals data sent to Control Center – **Complete**
3. EV Battery cycles (charging / idle / discharging) per test scenario – **Complete**
4. On periodic basis, BMS will report to Control Center status and charging state data – **Complete**

Observations and Results

Observations and Results

Within this use case, cycling of batteries (charging/discharging) was scheduled to be run 3 times a day (6 intervals) with a 1 hour standby between each interval. This was supposed to be done for electric vehicles but due to limitations, the scenario was modified to cycle the available battery resource at the SIS unit and collect the expected results and data.

The SIS unit provided a feasible platform for programming and scheduling a renewable energy resource along with grid connection and storage resource. By modifying the use case to use SIS battery instead of EV battery, the LADWP EV team achieved the use case data collection target, as well as saving time and resources. The SIS unit also enabled operators to put conditions on top of schedules and make flexible and on-demand rulesets for the scenario. In addition to these capabilities, the operator could have a complete set of data available on Sunverge cloud for download in 1, 5, 15, or 60 minute intervals.

Lessons Learned

- The use case required the electric vehicle battery to be charged and discharged in order to satisfy this use case. Instead of assigning a driver, the LADWP EV team used the battery from Sunverge to charge and discharge the battery.
- The SIS only had two options when charging or discharging the battery: a set value in watts or a percentage of maximum configured charge rate.
- There was no automated charge/discharge system available to be used for this use case.
- There was no EV capable of charge/grid-discharge with accessibility to internal EV data.
- The EV internal measurements were not usually available for research purposes.
- Not all EVs had the same internal data.

Best Practices

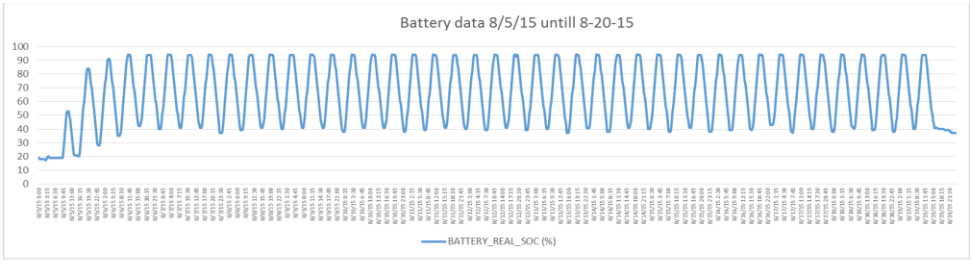
None established.

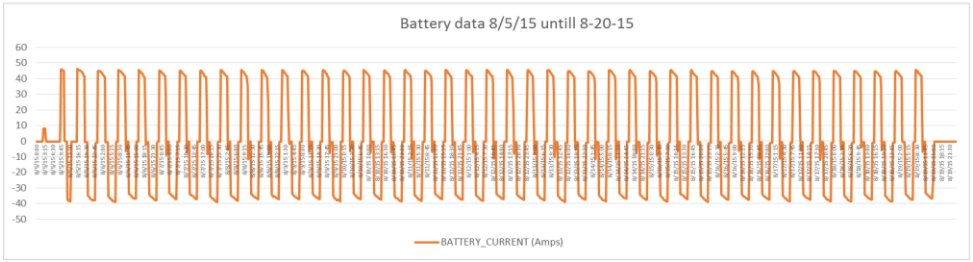
Results of Data Collection

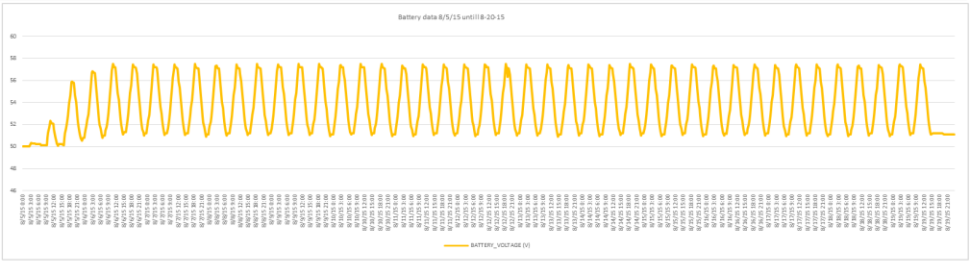
- Data from the Sunverge Battery. These data points included the battery state of charge, current, voltage, effective state of charge, power and temperature.
- Data on the Grid Line. These data points included charging real power, discharging real power, charging apparent power, charging frequency, discharging frequency, charging current, discharging current, charging voltage, discharging voltage, charging energy, and discharging energy.

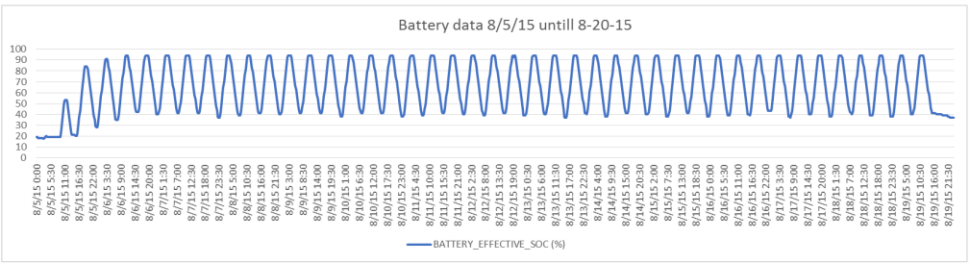
- Data from the meter and SIS. These data points included the SIS energy incoming, SIS energy outgoing, AMI energy incoming, and AMI energy outgoing.

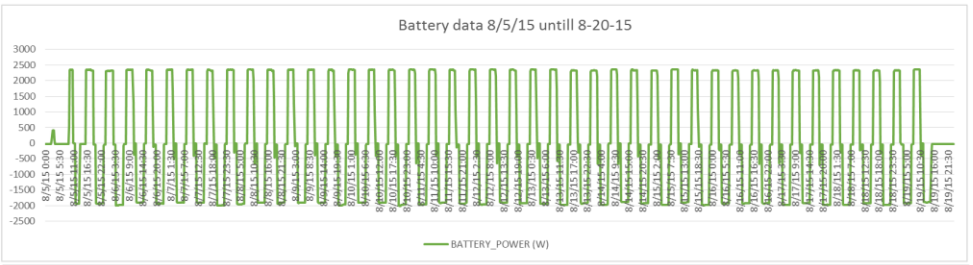
Data Collection Summary











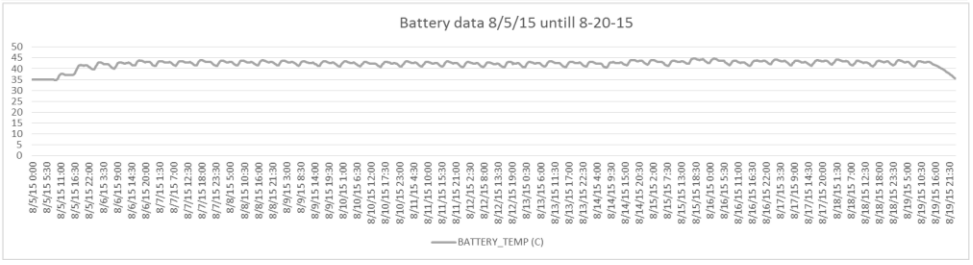


Figure 1: Battery Readings from SIS Unit From Aug 5 2015 to Aug 20 2015

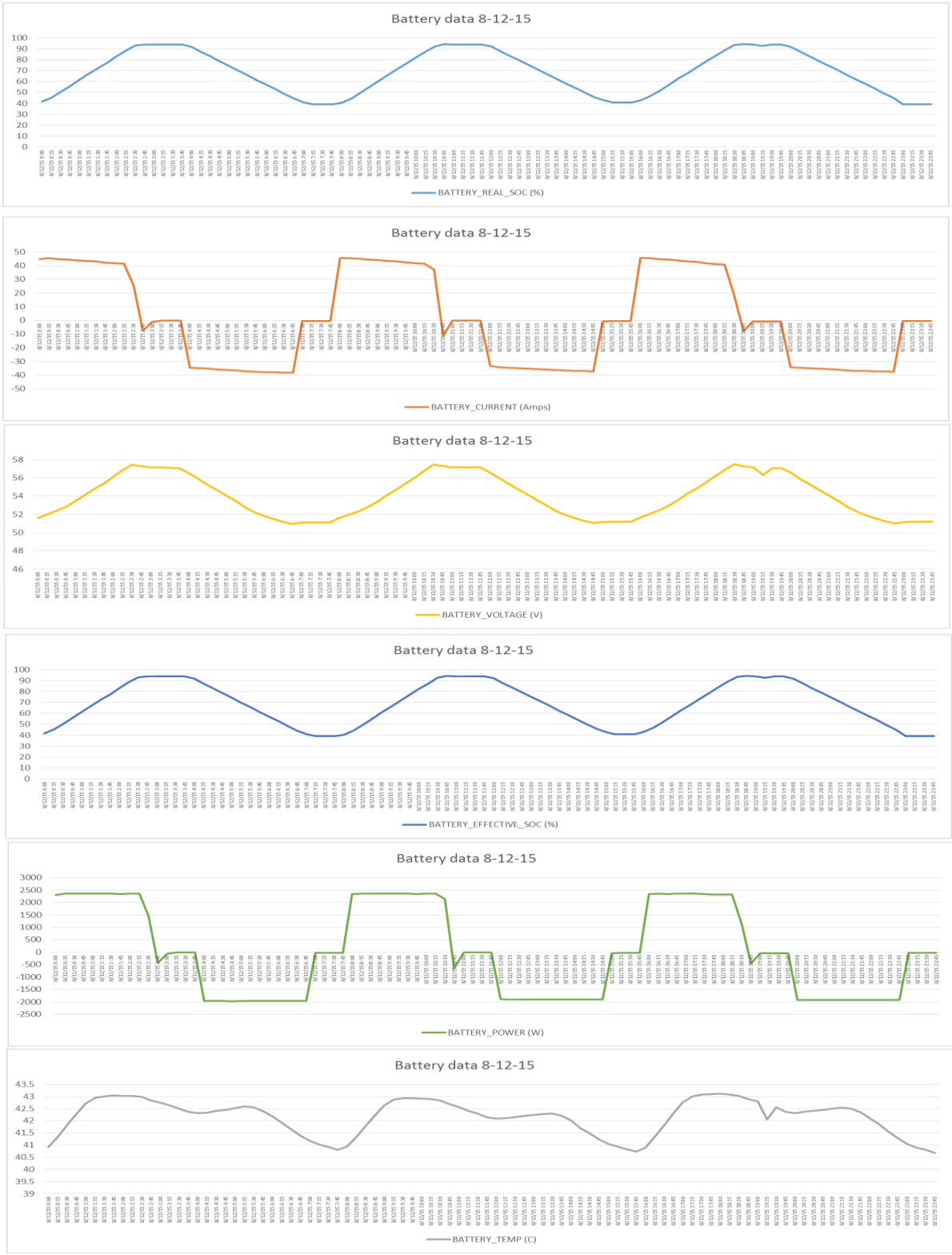


Figure 2: Battery Readings from SIS unit for Aug 12 2015

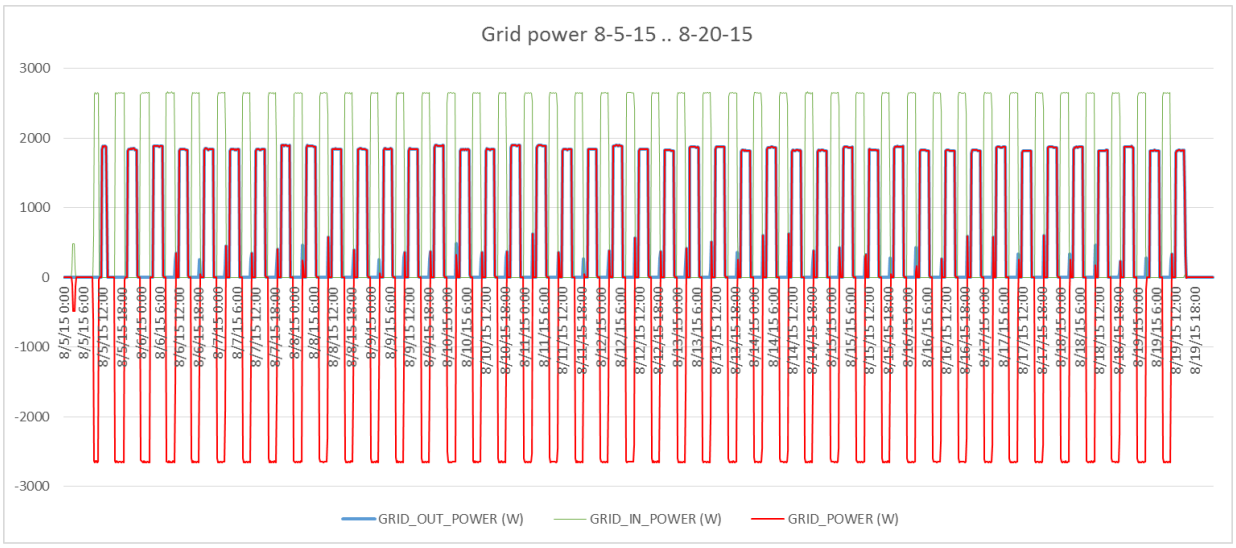


Figure 3: Energy Transfer between SIS Unit and GoF from Aug 5 2015 to Aug 20 2015

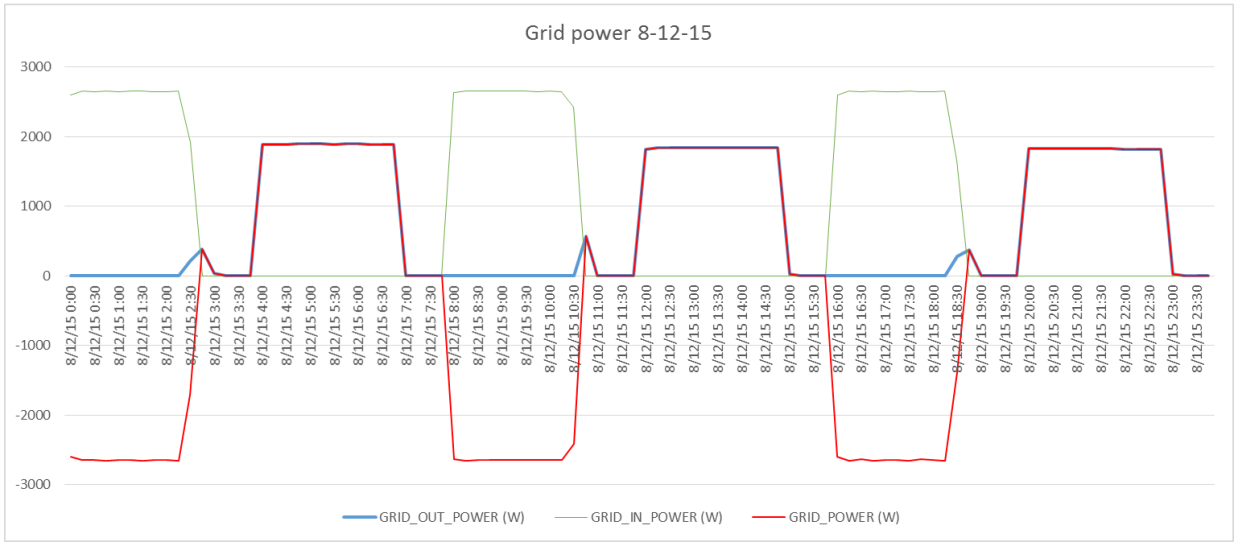


Figure 4: Energy Transfer between SIS Unit and GoF for Aug 12 2015

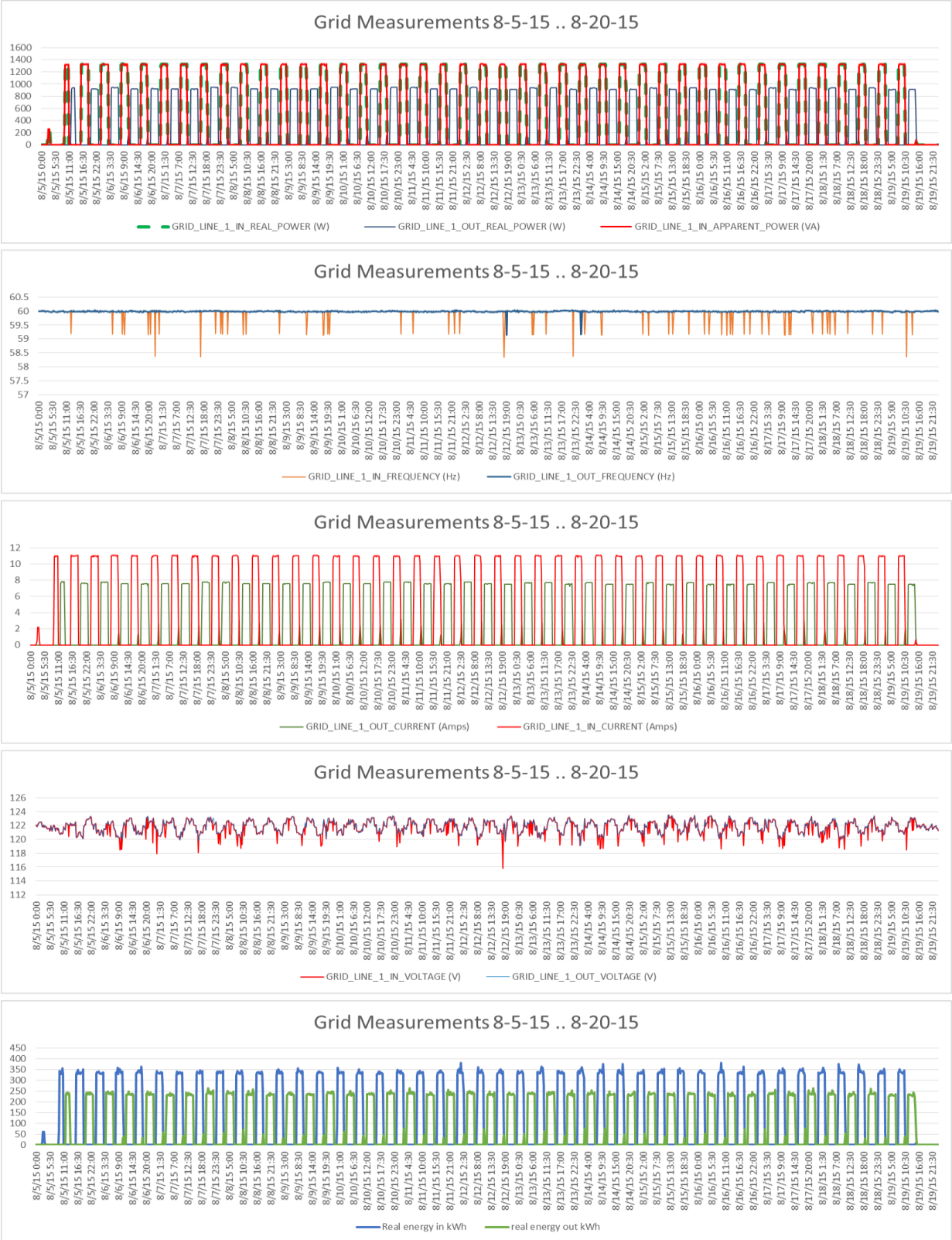


Figure 5: Power, Frequency, Current, Voltage, and Energy Transfer Readings between SIS Unit and GoF from Aug 5 2015 to Aug 20 2015

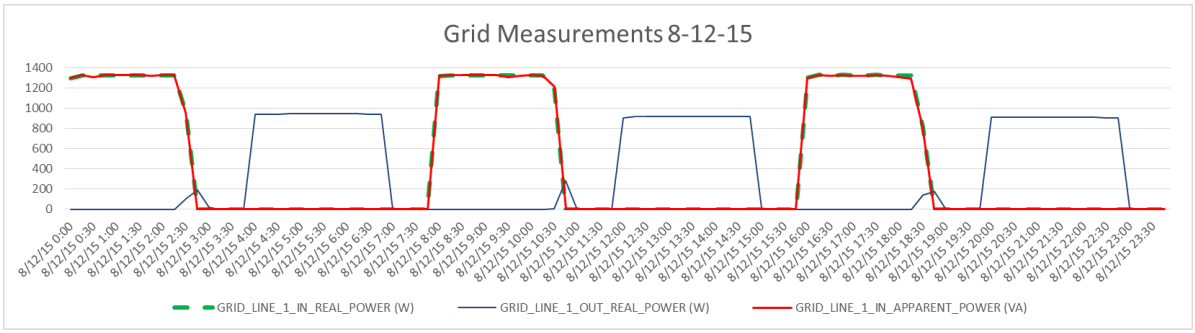


Figure 6: Power Readings between SIS Unit and GoF for Aug 12 2015

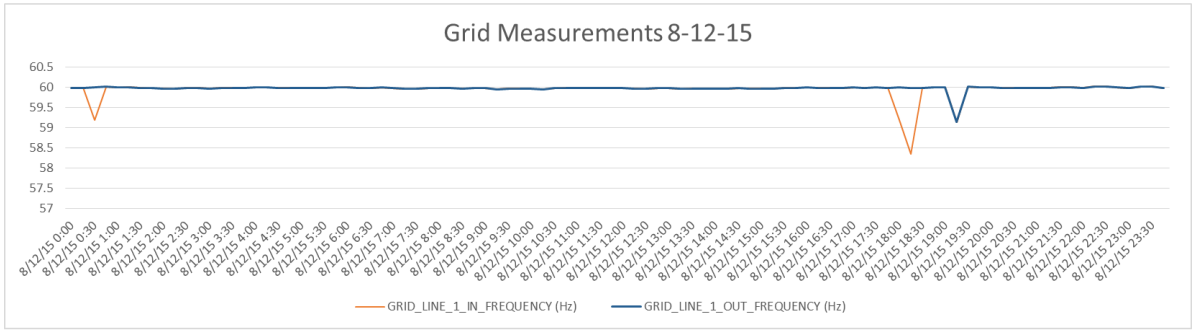


Figure 7: Frequency Readings between SIS Unit and GoF for Aug 12 2015

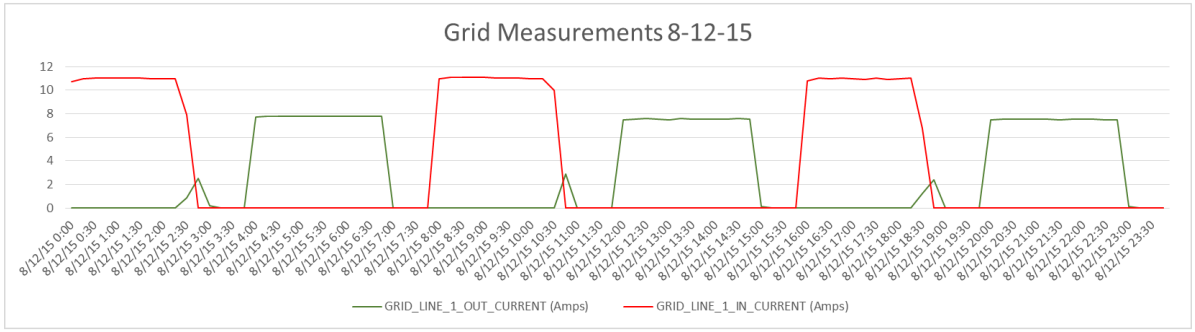


Figure 8: Current Readings between SIS Unit and GoF for Aug 12 2015

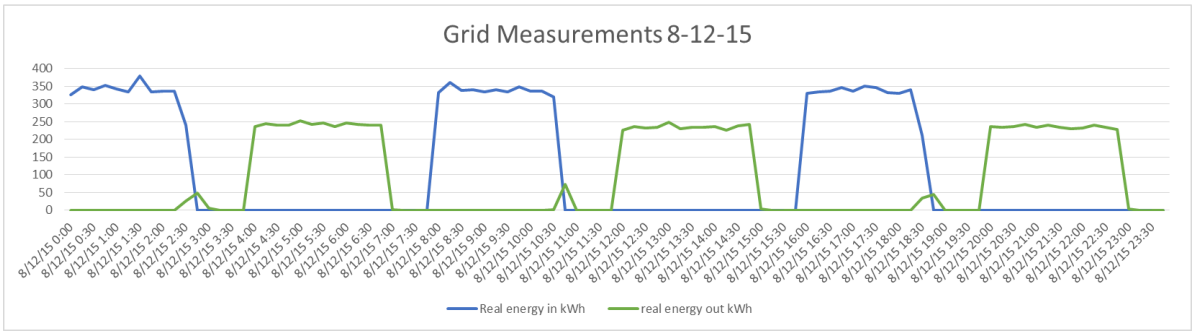


Figure 9: Energy Transfer Readings between SIS Unit and GoF for Aug 12 2015

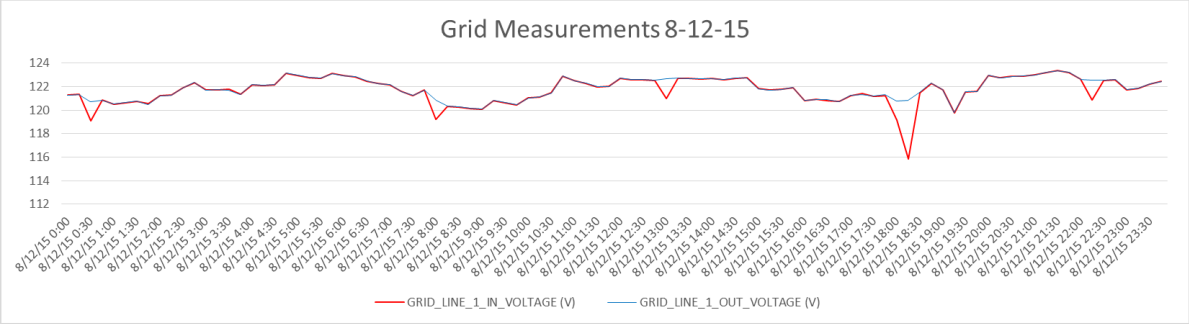


Figure 10: Voltage Readings between SIS Unit and GoF for Aug 12 2015

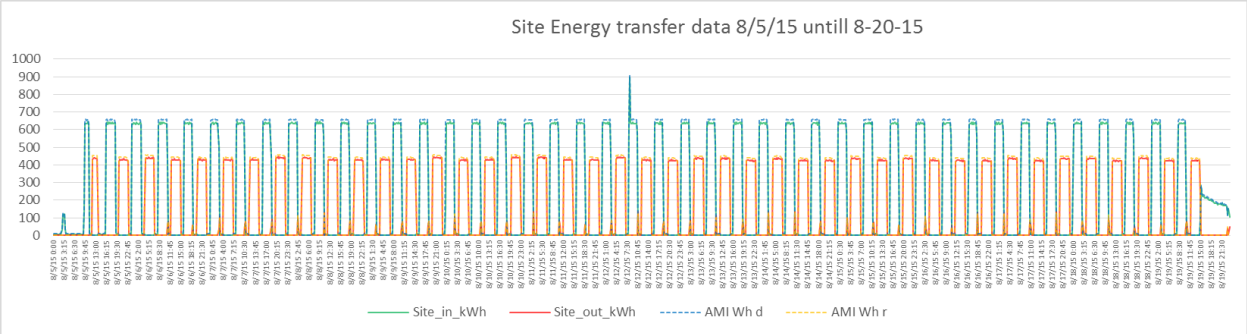


Figure 11: Energy Transfers In/Out between GoF and Grid from Aug 5 2015 to Aug 20 2015

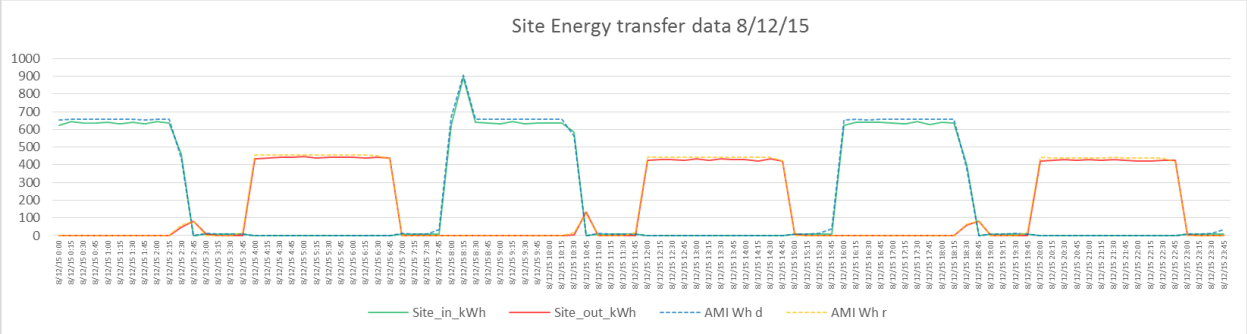


Figure 12: Energy Transfers In/Out between GoF and Grid for Aug 12 2015

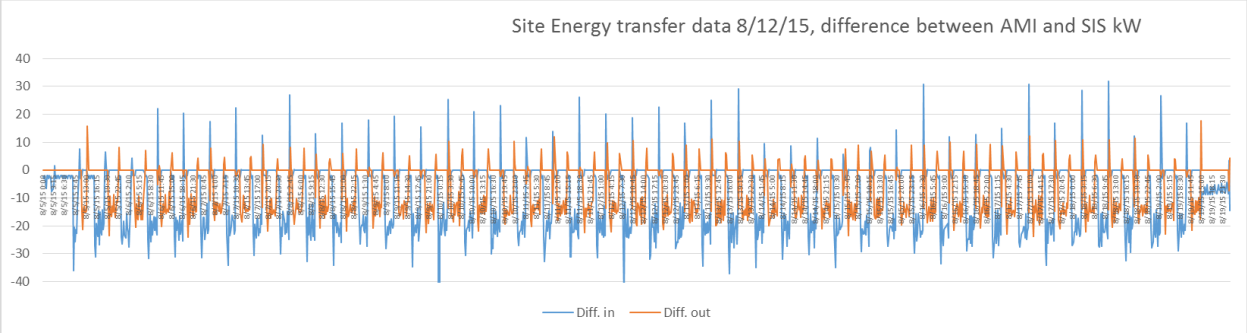


Figure 13: Difference between AMI and SIS Energy Readings from Aug 5 2015 to Aug 20 2015

List of Reports Published under this Demo

Demo 15 Report – Report date December 14, 2015

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

The collected data could be used in overall distribution system planning, asset management, infrastructure optimization, and cost effectiveness. The results would guide future systems development at LADWP and other utilities.

Realized Impacts and Benefits to Date

Only collected data from SIS battery was available to date. This use case impacted the view of EV usage, especially battery (EV) charging scenario using level 1 chargers, to be considered for futuristic EV planning.

Appendix AN Use Case #17

UC 17 TPR

Use Case (Demonstration) #17

Demo/Use Case Name: Integration of Electric Vehicle (EV) and Solar
Brief Description:

This use case applied the best usage of PV energy. Options include: charge battery, feed back into grid, and charge EV.

Methodology

-Assumptions

For this use case, the highest priority for the use of Photovoltaic (PV) energy was to have the SIS battery charged, and then have the EV as the second priority. It was assumed that the EV was leaving the charging station every day at around 2:30pm and there was a spike in demand at 4pm that will discharge the battery between 4-5 pm with maximum available power.

-Demo responsibilities

The EV Project team installed an appropriate grid-tie inverter, bi-directional AMI smart meters and solar unit at Garage of the future (GOF) facility located at Main street L.A. to demonstrate PV2Grid, PV2Battery and PV2EV operations.

Depending on the make and model of the EV, battery backfill might not be possible without modifying the BMS (Battery Management System) and other circuits on the EV. For resolving this issue, a Mitsubishi i-MiEV was selected as the EV and a dedicated V2G circuit was design by UCLA team to make the (grid-tied) vehicle to grid energy transfer possible. The Solar unit was also capable of being programmed to change the operational modes based on the real time and predefined conditions and availability of resources.

For this use case, the DWP EV team was responsible for collecting the available data from EV, Solar, and Grid. The scenario should have 1 session per day and multiple connections to the grid, battery and EV during the session. There was no minimum requirement for running this data collection period and the operation was performed for about 1 month (8/21/2015-9/24/2015).

Use case #17 required having a control center controlling the assets such as PV and battery, as well as a communication method to send commands and to collect and archive the data.

This use case was required to show that after running the use case, the PV would work properly, the control center was operating as planned, and data was being archived.

Vitals, consumptions, and status messages containing timestamps needed to be archived and reported.

All charging stations, batteries, and PV panels within the use case must report status and consumption to control center.

-Demo steps and flow

Data was collected from the available measurements in GoF, which included data from the solar unit and AMI meters during the data collection period. Electrical measurements including current, voltage, real and reactive power, frequency etc. from the solar unit and AMI meter was collected for each of the scenarios:

- Solar unit sending energy to grid; typically when there was excess energy available at GoF and both battery and EV were charged and no additional load exists in the Garage (PV2G).
- Solar unit charging Battery; this was the highest priority at GoF to have a reliable energy source capable of use for loads, EVs, or feeding back to grid.
- Solar unit charging the EV; typically when there was no need for charging Battery unit at GoF.

The designed and integrated scenario was completed to have a daily operating mode with the ability to charge and discharge of the battery, charge and discharge of the EV, and to use maximum PV energy based on our pre-defined priority to charge the battery, feed energy back to the grid, or supply the load. It also included augmenting the grid during the peak by battery with minimum personnel requirement. This scenario ran for more than 4 weeks.

-Planned approach

7. Analyze the collected data to be available for later usage.
8. Demonstrate the operation of the solar energy resource to feed local loads, charging batteries, EVs or sending to grid.
9. Finalizing the demonstration report.

-Key changes in Demo design and justification

This use case required that the vital data of the EV be reported to control center and also required the PV to charge the battery, the EV, or feed the grid once a day. Running this scenario had some operational and hardware limitations regarding the following topics:

- Driving vs. discharging
- Charge and discharge EV
- State of charge of EV battery
- Timing and schedule due to manual charge and discharge.

There were 3 options for charging and discharging the battery and collecting the vitals:

1) Charge EV and discharge by driving
2) Charge EV and discharge by discharge box provided by UCLA
3) Charge SIS battery and discharge SIS battery

The Use Case target is to have the battery charged at maximum usage of PV energy and to collect the maximum possible vitals.

- Method 1: To discharge the EV, a dedicated driver would be required to drive the EV every day for the duration of this use case. The specs of i-MiEV required the vehicle to be driven approximately 62 miles to discharge the battery, which was not a reasonable daily operational task.
- Method 2: the EV would be discharged by sending the energy back to the grid. This would be a replacement for method 1, because there would be no need to drive the EV.

Method 2 also had some limitations on connecting and disconnecting the charge and discharge cable, which needed to be done by a locally available operator.

In both method 1 and method 2, there was not enough monitoring capability on vitals of EV, such as voltage and current of battery, battery temperature, battery state of charge, ac and dc losses, etc.

- Method 3: this was not recommended due to its unrealistic nature, and since the team already had battery charge and discharge in this use case, the team could not use the same battery as the EV.

Method 1 was not selected due to limitations on assigning a daily driver during the running period of this use case.
Method 3 was not selected due to unrealistic nature and since the DWP EV team already had battery change and discharge.
Method 2 was selected, as the best option, while addressing the hardware limitations as discussed earlier in this document.

This scenario could be scheduled to be run automatically through the SIS (Solar Integration System) web interface and the vitals of battery and data will be available through SIS archive.
The EV was scheduled to charge and discharge by locally available personnel at GoF once in the morning and once in the afternoon for 5 working days of a week (Mon-Fri).
One of the biggest limitations in this use case was disconnecting from the grid automatically based on a trigger or condition of system. It was not possible to force the grid to stop feeding the load; as long as the load was plugged in, the grid (which may have PV or Battery as its resource) would continue to feed the load.

Technologies Deployed

-List of systems/equipment deployment,

- AMI Meter (Net meter)
- 1 EV Charger
- Solar panels, grid-tied-inverter,
- Energy storage(Battery), battery charger
- Electric Vehicle
- Various electrical sensors and metering system
- Network and data flow between GoF and control center.

Success Criteria

-Description of success criteria for this Demo

1. Develop a complete solar, EV, Grid, Battery system
2. Test and demonstrate PV2G, PV2B, and PV2EV strategy using developed system
3. Deploy/Install specified equipment
4. Using actual system to test the solar power flow strategy
5. Report collected data.

6. Network and data flow between GoF and control center.

-Progress vs. success criteria

1. Develop a complete solar, EV, Grid, Battery system **-Completed**
2. Test and demonstrate PV2G, PV2B, and PV2EV strategy using developed system **- Completed**
3. Deploy/Install specified equipment **-Completed**
4. Using actual system to test the solar power flow strategy **-Completed**
5. Report collected data**-Completed**
6. Network and data flow between GoF and control center. **- Completed**

-Changes in success criteria

Collected data for EV was reduced due the unavailability of internal EV data access and the solar point of connection data was considered as EV data.

Observations and Results

- Observations

- Sending PV energy into the grid was usually smoothed by storing the produced transient energy in local battery and by sending a non-variable power rate to the grid. For our system, the step of power flow from PV to the grid was 100W, meaning power variations due to changes in solar radiation would be increased or decreased in steps of 100W and the variations which were less than 100W would be stored in the local battery.
- The solar unit (Sunverge) was not capable of disconnecting the grid remotely and was not capable of stopping the feed to the load. The solar unit would always feed the load from available resources and functioned like an uninterruptible power supply (UPS).
- With a nondestructive modification in the scenario, this use case also helped the grid during the peak by battery with minimum personnel requirement.
- This scenario ran for more than 4 weeks. The variety of available data collected for this use case was reported.

-Lessons Learned

- The Solar unit (SIS) had some limitations when it was programmed to disconnect from the grid or stop feeding the load. Consideration should be made for future plans and operations when using this system.
- The EV internal measurements were not usually available for research purposes.
- Solar units available in the market were not capable of complete manipulation in their programs and usually had certain modes of operations that limit operational options.

-Best Practices

None established.

-Results of Data Collection

- Solar unit readings were available on the Sunverge (Solar unit provider) cloud and were accessible through the web portal and API.

-Data Collection Summary

- All power transfer and other electrical parameters were provided within the SIS cloud and a sample of PV voltage , current and power were depicted in figure 1:

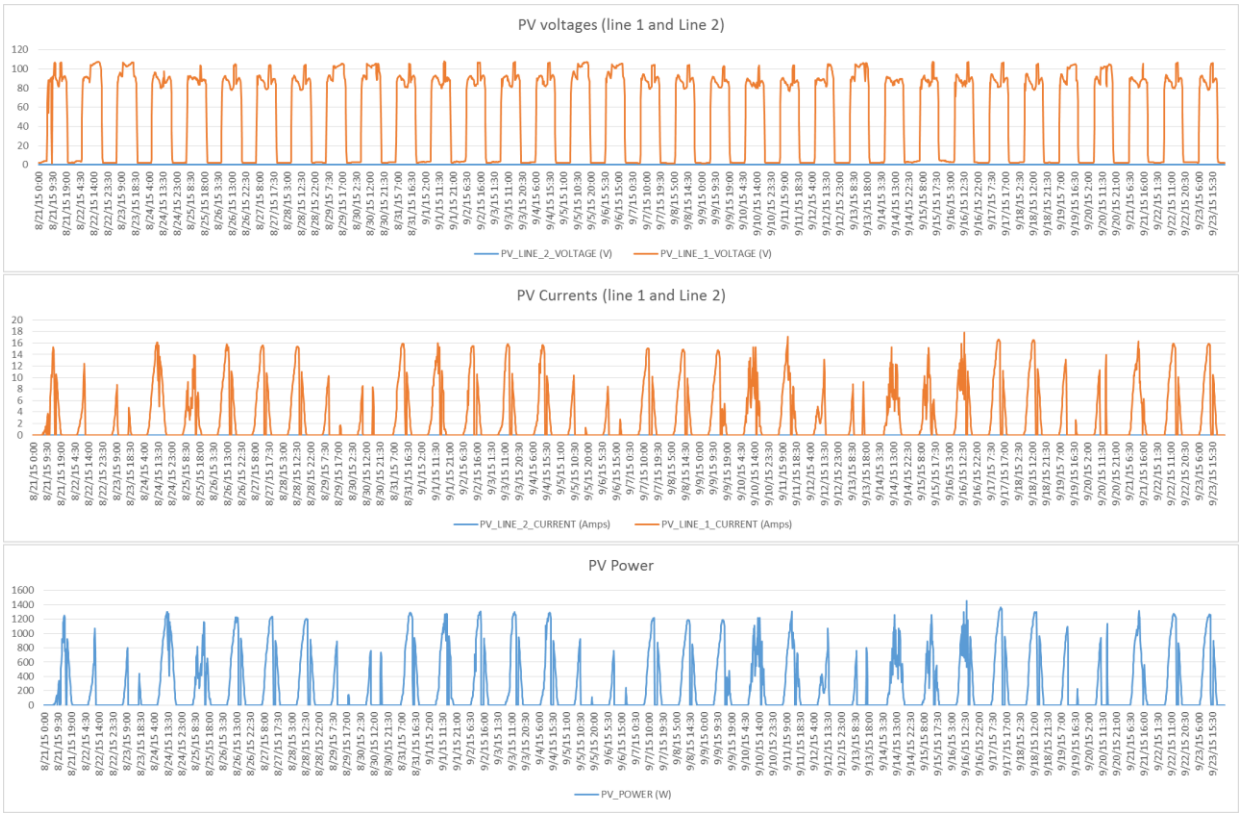


Figure 16 PV voltage, Current and power data

-List of Reports Published under this Demo

- Use case #17 data collection report

Impacts and Benefits

-List of Planned Impacts and Benefits for this Demo

- The collected data could be used in overall distribution system reliability, asset management, infrastructure optimization and cost effectiveness. The results would guide future systems development at LADWP and other utilities.

-Realized Impacts and Benefits to Date

- Only collected data from GoF were available to date. Various PV energy usage strategies were tested using available facility at GoF.

Appendix AO UCLA Electrical Vehicle Integration Project

Use Case Report

UCLA Electrical Vehicle Integration Project

Use Case # 10: Various Vehicle Charging

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UCLA Smart Grid Energy Research Center

March 31, 2016

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1. Document Overview

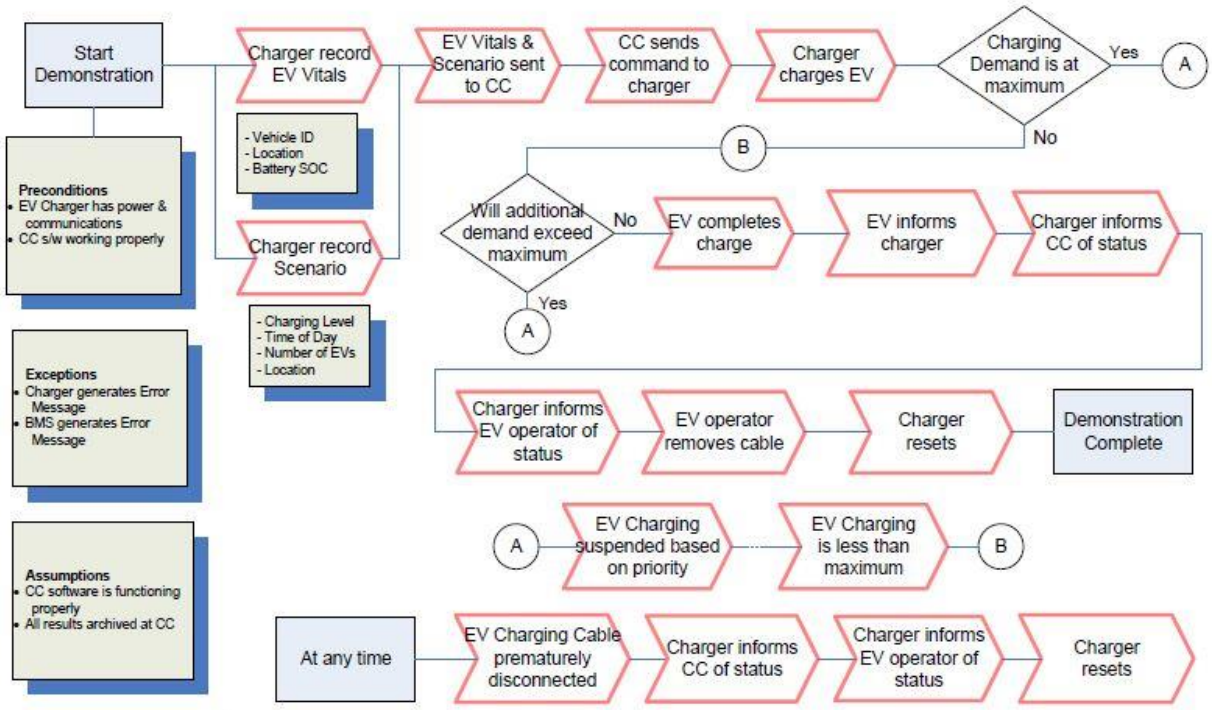
This document will present comparison of EV make and model observed in this project. The vehicles purchased/leased have been used to conduct research and perform tests with the design and development of the open architecture EV chargers as described in the design document. The communication between the vehicles and EV chargers has been studied, researched and tested. The various EV charging characteristics and behaviors from different vehicles have been observed and are taken into account in the design of the open architecture EV chargers.

2. Use Case description

2.1. Original Use Case Design

Based on the Design Document of SGRDP, Chapter 4, which is dated March 31 2012, Use case #10 is defined hereby.

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Use Case ID:	EV.10		
Use Case Name:	Various Vehicle Charging		
Created By:	Dennis Flinn	Last Updated By:	Dennis Flinn
Date Created:	6/16/2011	Date Last Updated:	8/10/2011
			
Actors:	Person(s) charging EV		
Description:	Monitor and compare the charging of various makes of vehicles available to the project.		
Trigger:	EV(s) connected to Charging Station via Charging Cable		

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Use Case ID:	**EV.10**
Pre-Conditions:	1. EV Charger has electric power 2. EV Charger has communications to Control Center 3. Control Center software is functioning properly
Post-Conditions:	1. Charging Station is ready for next EV Charging Session 2. Charging session results are archived at Control Center
Normal Flow:	10.1 Charging Station records EV Vitals 10.2 Charging Station records Scenario Data 10.3 EV Vitals & Scenario Data sent to Control Center 10.4 Control Center sends commands to Charging Station 10.5 Charging Station charges EV per commands 10.6 On a periodic basis, Charging Station will report to Control Center status and accumulative charging data 10.7 EV informs Station charging is complete 10.8 Charging Station reports results of charge to Control Center 10.9 Charging Station inform operator results of charging session 10.10 EV Operator removes & stores Charging Cable 10.11 Charging Station resets for new charging session
Alternative Flows:	1. Total EV Charging Demand reaches maximum value for location a. Individual EV charging suspended based on charging priority 2. Total EV Charging Demand is less than maximum value for location a. Will additional charging demand exceed limit for location (if not) resume charging based on priority 3. Charging Station Cable prematurely disconnected from EV a. Charging Station reports results of charge to Control Center b. Charging Station inform operator results of charging session c. Charging Station resets for new charging session
Exceptions:	1. Charging Station generates Error Message a. Charging Station reports Error to Control Center b. Charging Station inform operator of Error c. Charging Station resets for new charging session (if possible / depending on type of Error) 2. BMS generates Error Message a. BMS reports error to Charging Station b. Charging Station sends BMS error to Control Center c. Charging Station inform operator of BMS Error d. Charging Station resets for new charging session
Includes:	N/A
Priority:	High
Freq. of Use:	10 charging sessions per day
Business Rules:	Pending review of Joint Labor Management Committee
Special Rqmts:	Pending review of Joint Labor Management Committee

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Use Case ID:	EV.10
Assumptions:	1. Control Center software is functioning properly 2. EV Vitals, Scenario Data, and Status message contains timestamp 3. Use Case completed within Lab environment only.
Success Criteria:	All Charging Stations within Use Case scenario must report status and consumption to Control Center

2.2. Use Case Modification

This Use Case's design is similar to that of Use Case EV.3 where EV control center records EV charging sessions and power consumption. Additionally, this Use Case was assigned to UCLA SMERC Team around October 2015, there was not enough time to conduct a separate Use Case at that time. So, instead of make an effort to conduct a similar Use Case and demonstration, UCLA SMERC EV Team recommended the following medication:

- Use collected data to conduct analysis in terms of various EV make and Models's power consumption.
- Report J1772 communication issues with various vehicle
- Report energy efficiency and other observations based on the operation of grant vehicles.

These results are presented in the following subsections.

2.3. Use Case Setup

2.3.1. WINSmartEV™ Infrastructure

UCLA SMERC Team will use the same WINSmartEV™[1] Infrastructure for data collection in this use case. Please refer to Use Case EV. 1 through Use Case EV.5 for detail description of Use Case Setup. The following figure presents a high level over view of this infrastructure.

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[1] Please also refer to “Smart Charging and Demonstration Results” Report for details about WINSmartEV™ Infrastructure.

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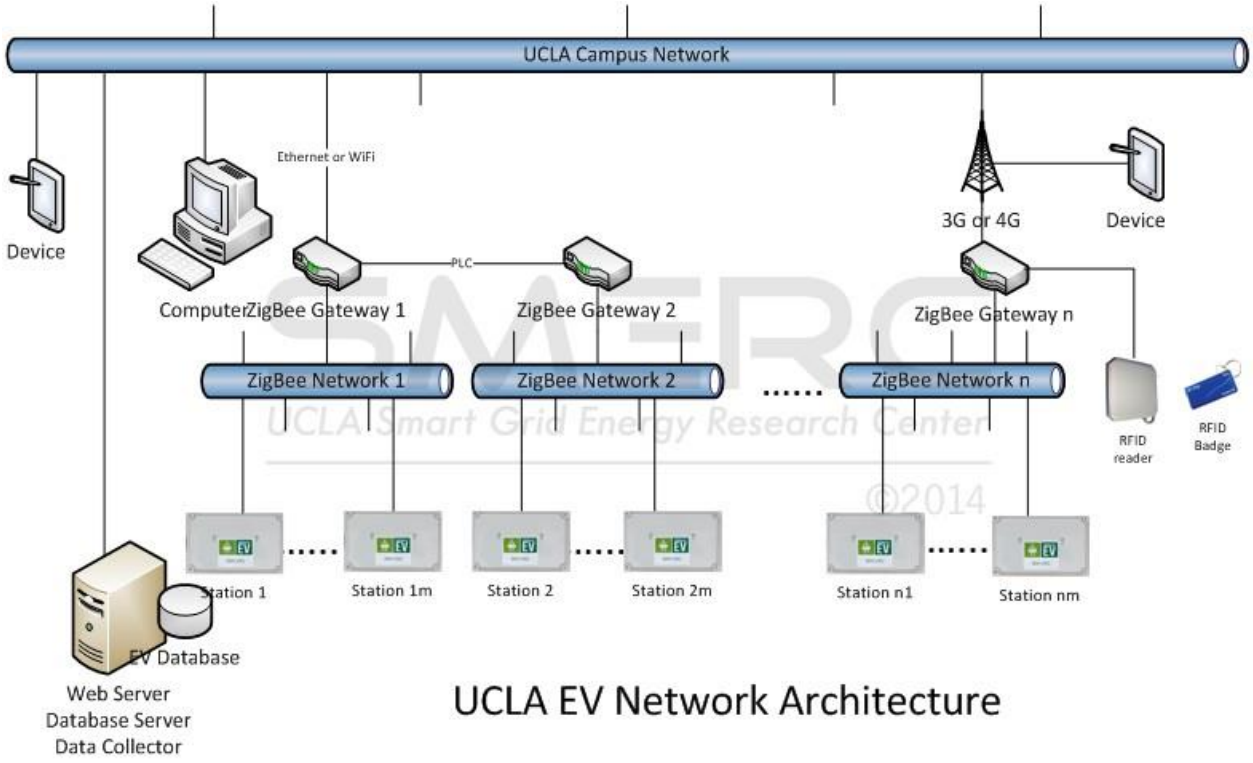


Figure 1. UCLA EV Network Architecture

As shown in Figure 1, built under UCLA campus network, the EV communication network utilizes campus Ethernet, WiFi or 3G/4G service to connect with ZigBee communication gateways which, in turns, connect with each individual EV charging stations through ZigBee communication protocol. The webserver and database server receive and send data through this hierarchical network connections. The mobile devices interact with the EV network through connection with 3G/4G or UCLA campus network.

2.3.2. Grant Vehicle

According to Task Order EV-UCLA-PS03-A, to date, UCLA EV Team has purchased/leased the following vehicles:

1. Nissan Leaf
2. Chevy Volt
3. Ford Focus
4. Tesla Model S - leased
5. 1st Mitsubishi MiEV – decommissioned from UCLA, waiting to be delivered to LADWP pending on agreement modification.
6. 2nd Mitsubishi MiEV – waiting for license plate to arrive.

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3. *Various EV charging - EV Make and Model*

3.1. Data Collection

There are

3.2. Energy Efficiency on Grant Vehicles

Estimated Vehicle efficiency based on monthly observation (readings from dashboard, driving experiences) on grant vehicle:

Grant Vehicles	Energy Efficiency (miles/kWh)	Battery size	Average Range when fully charged	Battery degradation and other battery related observations
Tesla Model S	3.81	60 kWh	208	No obvious degradation observed
Nissan Leaf	4.30	24 kWh	72	Obvious degradation observed, battery depth reduced by about 3-5 % after 2 years of testing
Chevy Volt	3.49	16 kWh	40	The battery condition is still very good.
Ford Focus	3.21	23 kWh	70	Minor degradation observed
Mitsubishi i-MiEV	3.97	16 kWh	61	Used for V2G experiment. Not enough data to make observation

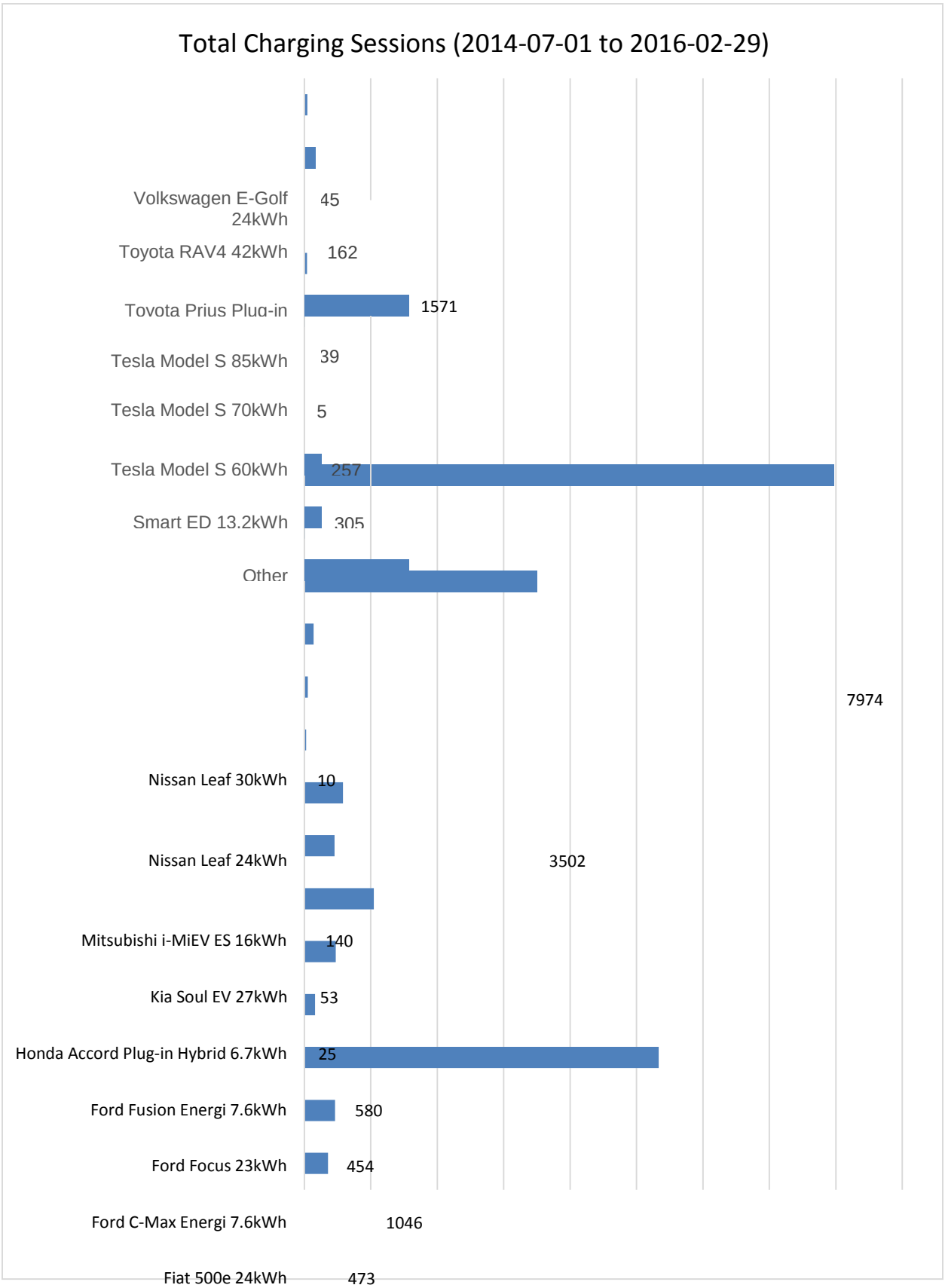
Overall Nissan Leaf has the highest Energy Efficiency overall. However, it all depends on EV driver's driving pattern. Chevy Volt's battery is quite well protected, it charges only at 3.3 kW level. There are no obvious degradation of battery observed.

3.3. Various Vehicle Charging based on Charging Sessions

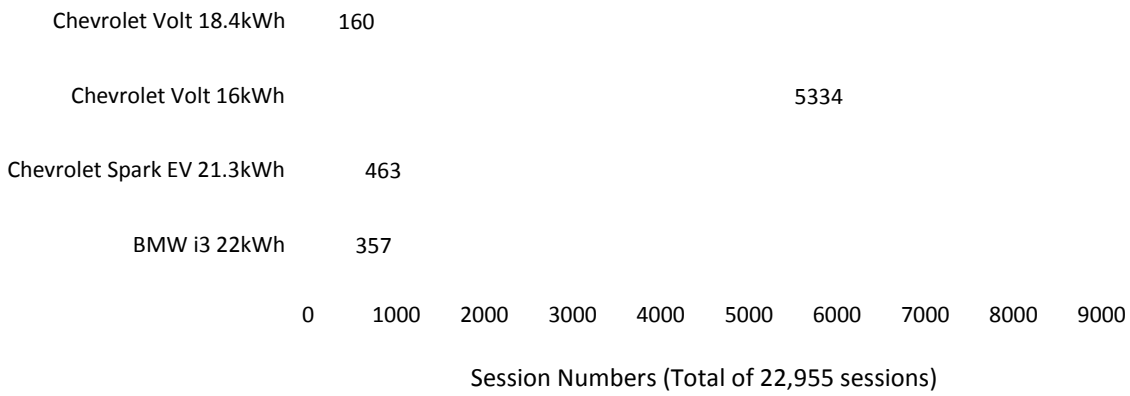
The following chart are created based on information collected valid charging sessions. Invalid charging session are defined as a session that consumes less than **0.1 kWh** of power. This is usually resulting from invalid charging operation or charger malfunction. Data Collection period is **2014-07-01 to 2016-02-29.**

The model "Other" means that EV user do not wish to disclose their EV model or the vehicle belongs to UCLA housing fleet.

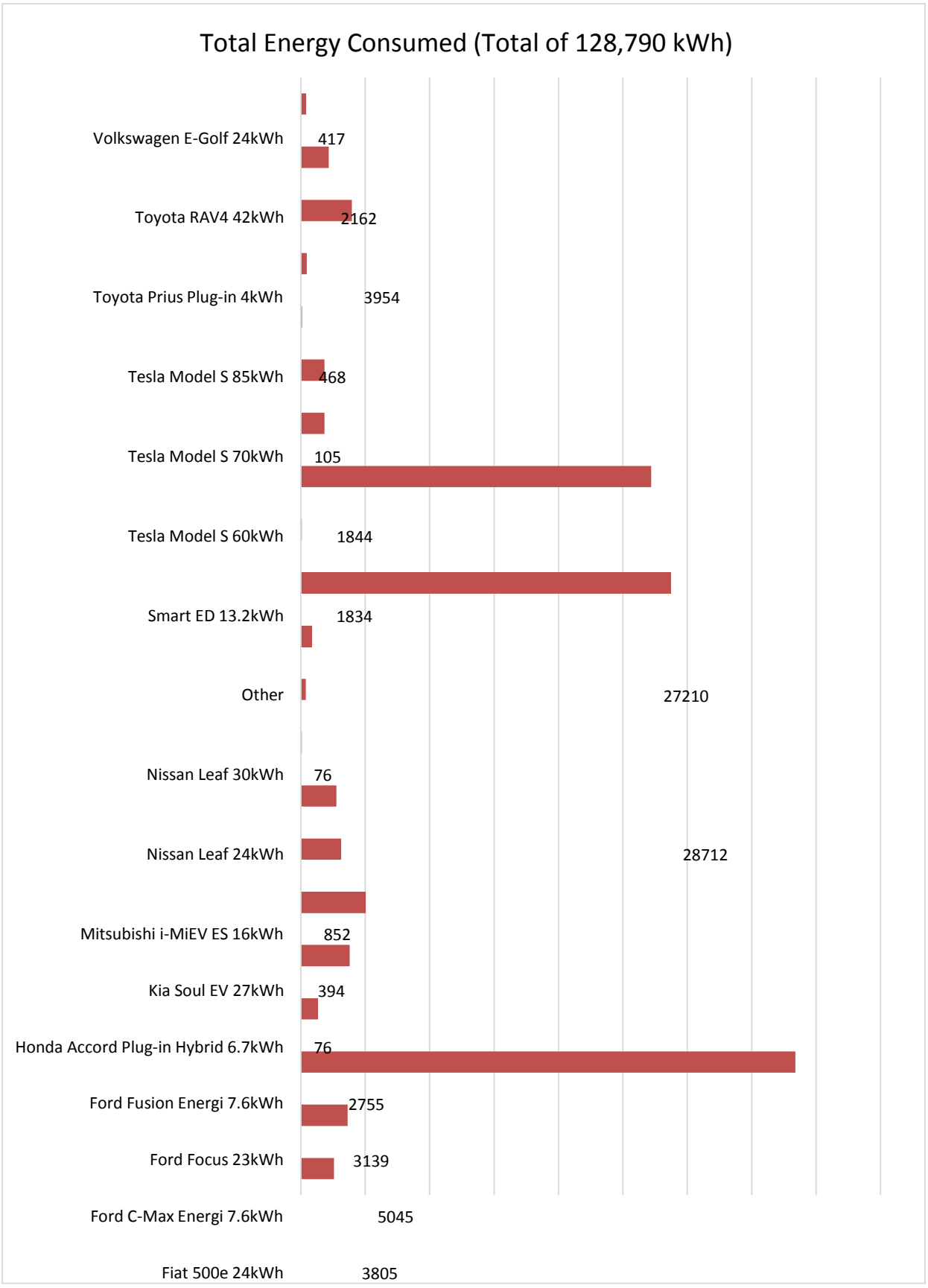
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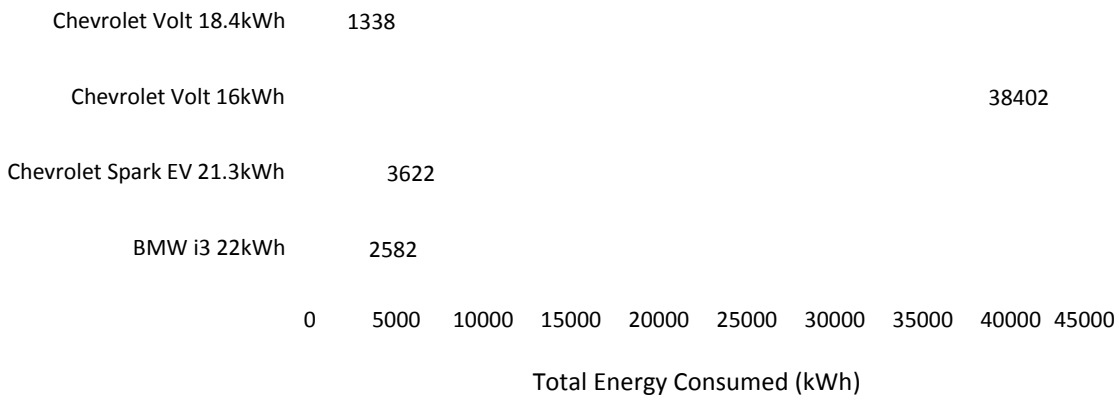
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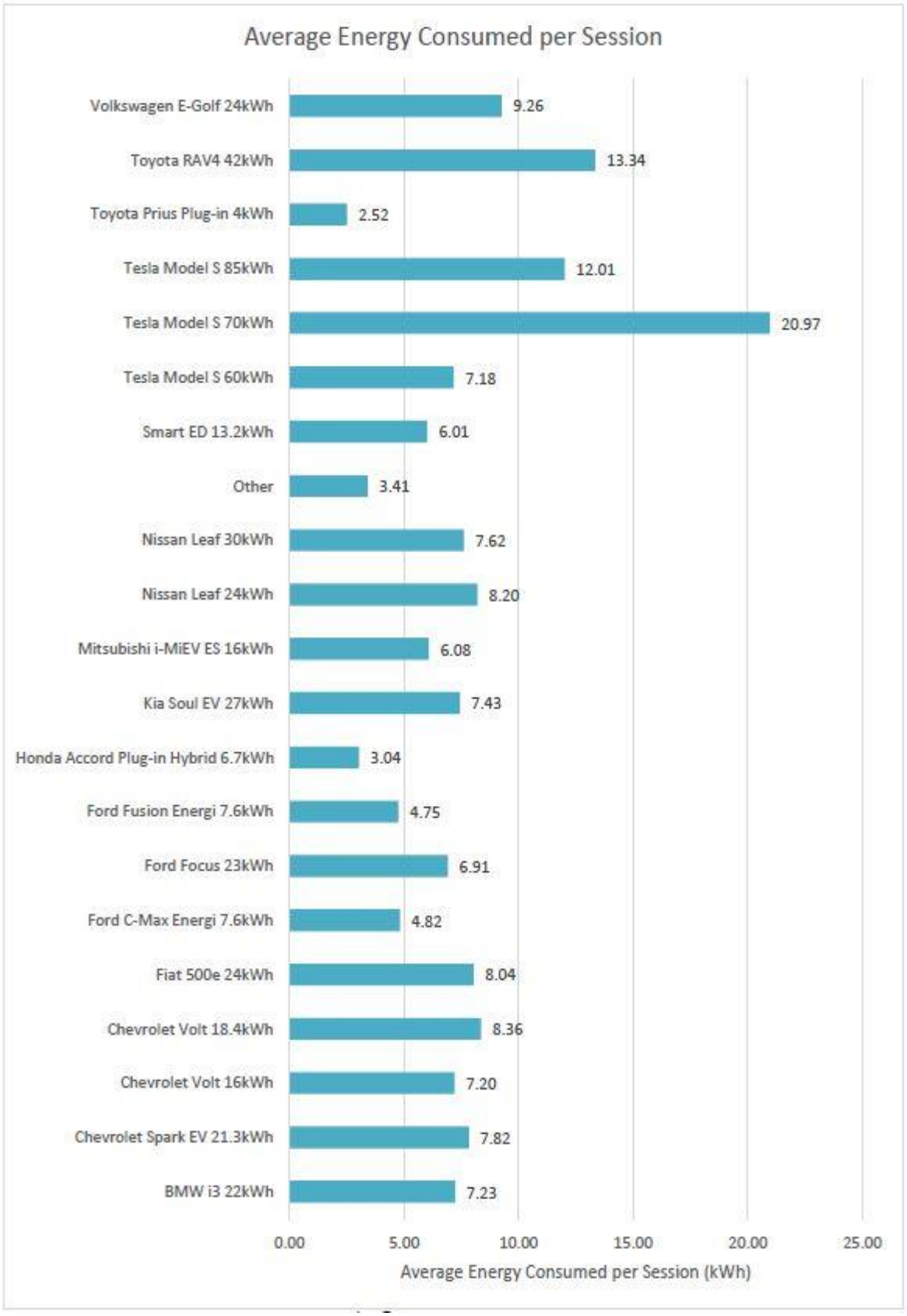
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The following section describes the issues we have encountered integrating EV models into our smart charging infrastructure.

3.4. Observation of EV make and Models

Chevy Volt, Ford Focus, MiEV and Nissan Leaf Charging

Some of the specific observations we have found include impacts on voltage drop on the ability to send power to the vehicle and we have found that in certain vehicles such as the Chevy Volt the sensitivity to voltage fluctuations on the ability to get a charge is high; the inability to re-start a stopped charging session after the charging cable is disconnected on the Ford Focus; and this is contrast with the flexibility of input characteristics such as the above on the consistency of the charging behavior of Nissan Leaf. UCLA EV team has been continuously conducting experiments such as the above, and continues to do so, and will include these results in the final deliverable reports. Such variations in behavior are also resulting in us modifying the nature of the architecture of our system so as to make the overall architecture more robust and reliability in the presence of multiple EVs. Additionally, where feasible, we have reached out to the various EV manufacturers about some of our findings and are pursuing various lines of discussion on potential solutions by way of technological solutions and/or standards modifications so as to standardize the communications between the EVs, the charging stations and eventually the smart grid.

Drivers with different vehicle makes, different commute distances, different work habits such as where they charge (at home, in the office, in public places, etc.) and different work hours have different requirement for charging preferences. To be able to accommodate such a multitude of influencing factors on the smart charging scheduling, the purchased and leased vehicles are assigned to researchers and staffs in UCLA EV project team with various EV charging needs/preferences to test the scheduling algorithms. The driver also utilizes the mobile application developed in this research to specify his/her charging preference based on the make and model of the vehicle that was assigned to him/her. Eventually, the decision of where to charge, when to charge, how much to charge and which algorithms to be used to charge an EV would depend on a combination of personal driver preferences, facilities available for charging in parking facilities (such as at work, at home and at public places) and the programs offered by the grid operators including TOU pricing, renewable energy availability, etc. These and related topics are being researched.

Due to the significant variations in features among the different vehicles, in addition to the above usage for charging an EV, Mitsubishi MiEV is also used for V2G development and research, Nissan Leaf is used to level 3 CHAdeMO interface and backfill research, Chevy Volt is used as a influencing factor for being a hybrid vehicle (perhaps this may result in a less urgent charging need than pure electric and it could have an impact on scheduling algorithms especially when prioritizing who should get the energy first during limited time availability of energy such as perhaps during a Demand Response event), and Tesla Model S is being used currently for design and test of higher charging power experiments. In addition, Nissan Leaf and Chevy Volt were also both used to develop SOC modules to transmit battery status of charge (SOC) and BMS fault signals to the EV chargers and then back to the control center as an

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input to smart scheduling. These are a subset of the examples of the specific research experiments ongoing currently and to be performed and will be addressed in details in the final report.

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The following sections are summaries of issues related with EV make and model UCLA has encountered. The problem with Tesla Model S will be discussed in a separate section in this report.

3.4.1.1. Nissan Leaf

Nissan Leaf is used for smart charging (Level I, II and III) demonstration. The charger design has taken into consideration the flexibility of charging behavior of Nissan Leaf. Due to it is compatible with CHAdeMO protocol, it is also used for research in Level III. It is also used for research in battery State-of-Charge (SoC) monitoring. SOC modules has been designed for Nissan Leaf to transmit battery SOC and BMS fault signals to the EV chargers and then back to the control center as an input for smart scheduling. Preliminary observation and tests were conducted to study Nissan Leaf's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support and limited time, it is not feasible to perform V2G demonstration on these vehicles at this time.

3.4.1.2. Chevy Volt

Chevy Volt is primarily used in smart charging (Level I and II) demonstration. Charger design has taken into consideration the impacts of unable to charge due to voltage drop (below 190 VAC) on Chevy Volt. On algorithm design end, Chevy Volt is considered as an influencing factor for being a hybrid vehicle (less urgent charging need than pure electric). SOC modules has been designed for Chevy Volt to transmit battery SOC and BMS fault signals to the EV chargers and then back to the control center as an input for smart scheduling. However, at a recent vehicle software update, the SOC information was further encrypted and we are unable to retrieve this information right now.

Another observation of Chevy Volt is its alarm system that will be activated when the EVSE lost it power. This problem can be resolve by changing the setting inside the vehicle.

Due to the fact that it has only AC onboard single-direction charger, it is not used for V2G demonstration. Preliminary observation and tests were conducted to study Chevy Volt's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support and limited time, it is not feasible to perform V2G demonstration on these vehicles at this time.

3.4.1.3. Ford Focus

Ford Focus is primarily used in smart charging (Level I and II) demonstration. Charger design has taken into consideration the fact that it is unable to re-start charging session after charging disconnection of Ford Focus. Another observation is that Ford Focus will not be able to enable charging if the charging session power is not provided within 5 minutes after it is plugged in.

Due to the fact that it has only AC onboard single-direction charger, it is not used for V2G demonstration. Preliminary observation and tests were conducted to study Ford Focus's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support and limited time, it is not feasible to perform V2G demonstration on these vehicles at this time.

3.4.1.4. Mitsubishii-MiEV

Mitsubishi MiEV is primarily used for demonstration of power back-feeding, smart charging (Level I, II and

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III) and design of renewable integration. The Mitsubishi MiEV is equipped with both J1172 and CHAdeMO,

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making it compatible with three levels of charging. The V2G function developed is based on the V2X box. Currently, the V2X box was used to withdraw the AC 100 V power from the vehicle and then the AC power was converted into 48 V DC and then connected through a grid-tie inverter to conduct V2G project.

3.4.1.5. Fiat 500e

The Fiat 500e model can only charge using the full power source. In addition, the EV user must submit a charging request to make the pilot signal draw a high current before plugging-in the cable. The initialization charging process fails if the duty cycle of the pilot signal is small, which indicates only low charging current is available. If the initial duty cycle is high and later changes to a lower one, the Fiat EV will generate the error messages of "Service Vehicle Electrical System" and "Service Your Charging Station".

Data collection on level 1 - Balancing utilization

On days when the number of public EVs is low, our own EV drivers try to plug into the level 1 so that we have sufficient data that is meaningful on a statistical basis for level 1 chargers, as the public typically plugs into level 2 if they are available.

SOC calculations

Given that J1772 is currently not providing SOC, and given that the SOC plugin does not work uniformly for ALL EVs, we enter the SOC information manually in the App. Given that there is no way to verify if the public users are entering the information correctly, our own team driving our own EVs diligently enters the correct information so that our data is accurate. Eventually, this difference will be used as a basis for data analysis.

Switchover time

The switchover time for between start and stop of multiple EVs plugged into a charger might vary with the type of EV. We have observed unusual behavior and so our own EV drivers need to test by manually removing and inserting the J1772 plugs. This is not feasible to do with other EV owners as it may wear out their J1772 plus. For that reason, our own research team needs all the models.

3.5. Tesla Integration Issues

3.5.1. Summary

	Issue	EVSE #	Date Detected	Symptom
1	Charging Cable Fault	PS8 201	Oct 20, 2014	No power into battery through cable

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2	Failure to start charging after deactivation on a Level II EVSE	PS2 202	Aug 8, 2014	Algorithm cannot restart charging on Level II EVSE after modifying duty-cycles

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3	Failure to switch charging sessions on a Level I EVSE	PS9 401	Sept – Nov 2014	Algorithm cannot activate charging for Tesla after multiple sequences of activation and deactivation
4	Failure to charge on Level II EVSE with multiple connected EVs	All Level II EVSEs	Oct 2014	Tesla fails to start charging session when there are already EVs charging on the same EVSE
5	Sporadic failure to charge on Level II EVSE	All Level II EVSEs	Oct 2014	Tesla sometimes fails to start charging session even if no other EVs are present
6	Fail to consume energy on Level II EVSE	PS4 all plugs	June 2014	Tesla can start charging session but cannot get any power
7	Demand Response (DR) Capability	All UCL A	November 2015	Tesla only supports limited demand response functions.
8	DC V2G Capability	V2G Charger	November 2014	Tesla does not support DC V2G
9	CHAdeMO V2G Compatibility	V2G Charger	November 2014	Tesla charger is not compatible with EVSEs using CHAdeMO protocol

Charging Cable Fault

We are unable to initiate charging on Level 1 EVSEs that use the price-bid algorithm. The failure occurs as follows. When a Tesla user submits a charging session to the control center, the meter/relay of the EVSE initially turns on, but the algorithm, running on the server, automatically closes the session. If we attempt to reactivate the charging session using the mobile app, the EVSE's charging light turns on, but the power cable does not function properly – the light on the power source adapter becomes red, the charging port starts blinking red, and the dashboard reads "Charging Cable Fault." With regard to the dashboard's message, the Tesla's user manual states that a proper charge setting requires the charging port to have a stable green light and the adapters to display flowing green arrows.

To verify the charging cable failure, we conducted experiments using a second charging cable from Tesla. We found that the second cable functions properly. Therefore, the solution for this issue is to replace the charging cable. While this may be the case for this situation, it is not clear currently what the reason for such variability is. Causes could be related to the variation in the software within the vehicle being

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upgraded but working for a newer model of the charger while not working for an older model, or a myriad of other possibilities which will be explored in the remainder of this project.

Unable to start charging on Level II EVSE

This issue occurred on Outlet 1 of the Level II EVSE in Parking Structure 4. The Level II EVSE was running the price-bid algorithm that dynamically allocates duty cycles to each plugged in EV. Generally, if the duty cycle, assigned through user preferences, is lower than 10%, the algorithm disables the charging session until the other EVs finish charging or leave. During our observation, when the EV connected to the 4th outlet finished charging, the server-side algorithm correctly enabled the charging session for the Tesla connected to Outlet 1 and set the duty cycle to 13%. However, the charging current remained lower than 10% during the initial 6 to 10 seconds; at which point, the algorithm assumed the Tesla had fully charged and closed the charging session as show in Figure 2. This delay in the charging current seems to affect the Tesla, because we have observed the charging current rise in about 3 seconds for other EVs, such as the Nissan Leaf and Chevy Volt.



Figure 2 Algorithm closes the Tesla's charging session

We devised a temporary solution for the Tesla by prolonging the delay time in the price-bid algorithm to allow time for the current to increase. We also conducted experiments and discovered that the Tesla has a complex internal battery management system (BMS), which adaptively controls charging behaviors based on the power source; thus, the time required to initiate charging will be different at varying times. However, it is not fully clear as to whether this approach is generalizable and also we need to conduct experiments comparing with different EVs. This can be a potential challenge to EV charging.

Failure to Switch Charging on a Level I EVSE (Price Bid Algorithm)

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This issue occurs on the Level 1 EVSE that uses the price-bid algorithm. This algorithm allocates energy (charging time) to EV users based on their price preferences and switches charging sessions among users who are connected to the same EVSE. In the case of the Tesla, we have observed that after switching several times, the vehicle will not resume charging. We have not encountered this issue with other EVs, such as the Nissan Leaf or Chevy Volt.

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To investigate this problem, we examined the Tesla's historical charging records when charging on a Level EVSE with the price-bid algorithm. In each case, we observe that the Tesla successfully reactivates charging four times and fails on the fifth attempt. We are trying to determine why this is occurring and this requires further research and a large number of test cases and data collection.

Figure 2 Charging session on 10/15/2014



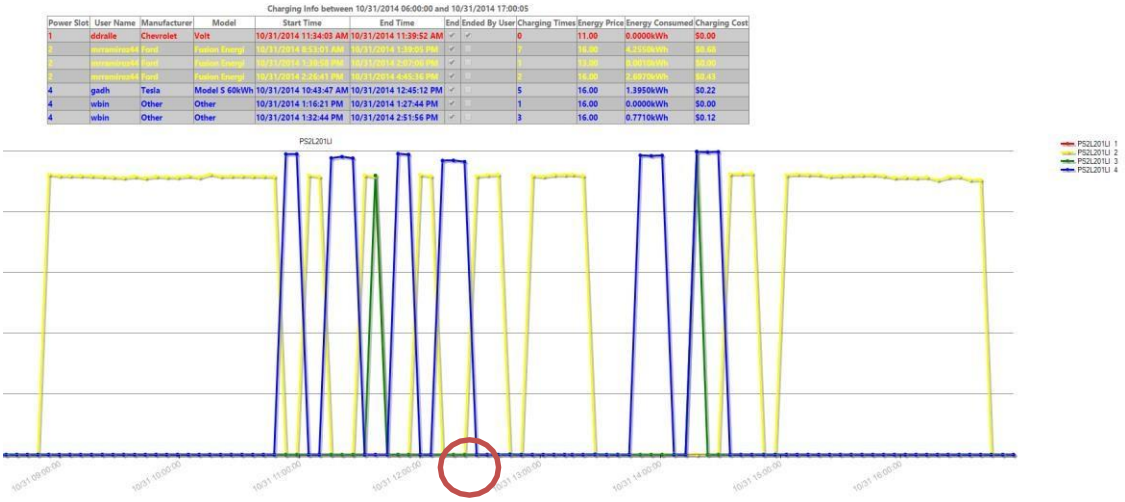


Figure 3 Charging Session on 10/31/2014

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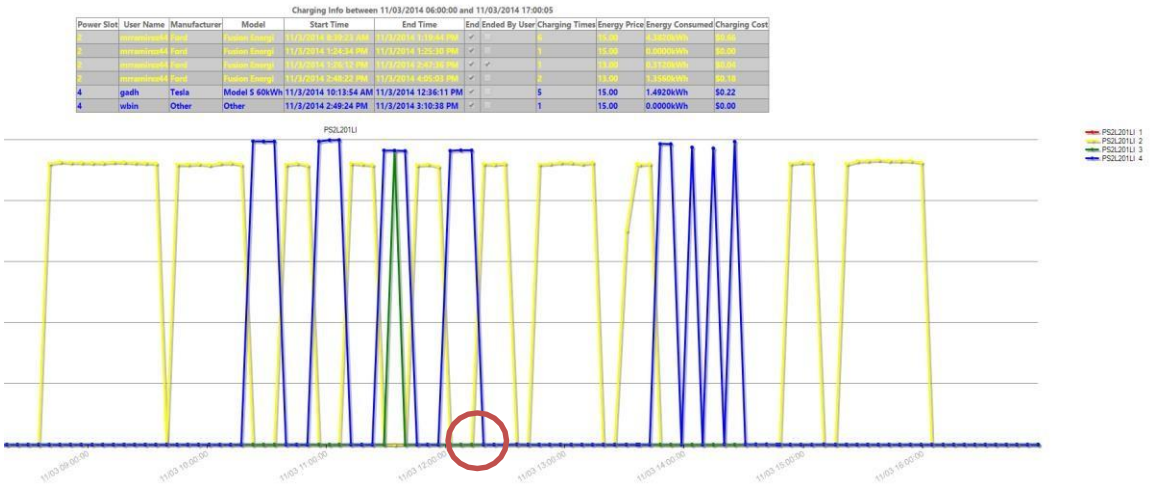


Figure 4 Charging Session on 11/3/2014

We verified the scenarios in these charging sessions through an experiment in which we virtually activated and deactivated the EVSE's meter/relay every five minutes, simulating the switching behavior of the price-bid algorithm. The following table shows the experimental data.

Experiment simulating the switching behavior of the price-bid algorithm on a Tesla

Timestamp	Meter/Relay Status	Dashboard Message
13:50	On	charging
13:54	Off	charge interrupted: check power source
13:59	On	starting to charge, 2 sec, charging
14:04	Off	NO WALL POWER: power interrupted,check power source
14:09	On	starting to charge, 2 sec charging
14:14	Off	NO WALL POWER: power interrupted,check power source
14:19	On	starting to charge, 2 sec, charging
14:24	Off	charge interrupted: check power source
14:29	On	startting to charge, 5 secs, charge stopped.

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14:32	Off	ready to charge
14:35	On	startting to charge, 10 secs, charge stopped. **(Fail to Charge)**

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14:36	Off	ready to charge
14:38	On	starting to charge, 10 secs, charge stopped. **(Fail to Charge)**

As a temporary solution for this issue, we increased the time quantum from 30 minutes to 60. However, we must consider the tradeoff between the switch times and length of each time quantum. For example, if we decrease the length of each time quantum to 30 minutes, Tesla users will likely reach the maximum limit of five switch times. On the other hand, if we make the time quantum too long, we risk harming the equitable consumption of energy among other users; they will have to wait very long to get energy, which will affect their travel schedules. The length of time interval needs to be investigated and will be varied along with a few other variables for further research. This also requires a substantial amount of data collection and analysis.

3.5.5. Failure to charge on a Level II EVSE with multiple connected EVs

We have observed the Tesla failing to start a charging session when other EVs are already charging at the same EVSE. We believe that the Tesla does not accept our start charging process when the EVSE is already running, because the EVs connected to outlets 2-4 go through a redistribution of the duty cycle at the end of the start charging process. To solve this issue, we have moved the redistribution of the duty cycle for charging multiple EVs to the beginning of the start charging process. It is important to solve this problem as our approach is designed to be grid friendly – i.e. the charging rates are controllable and flexible and in the absence of such capability, the Tesla charging may not be scalable when it comes to grid-friendliness. This problem is being researched further.

3.5.6. Inconsistent Charging on Level II EVSE

We have observed that the Tesla sometimes fails to initiate a charging session regardless of other EVs charging on the same EVSE. We attribute this case to the Tesla having a higher standard requirement for the pilot signal voltage as compared to other EV brands. To resolve this issue, we replaced the output resistors and amplifiers of the pilot signals to meet the SAE J1772 standard.

3.5.7. Failure to Consume Power on a Level II EVSE

We have observed that the Tesla sometimes fails to consume power on a Level 2 EVSE in Parking Structure **4.** We have identified two potential reasons for this problem. First, it could be a characteristic of our EVSE which allows dynamic current modification even though we have implemented as per the SAE standard. In comparison, the other EVs work appropriately which implies that differences in the implementation with the Tesla charging technology is probably the cause – this needs to be investigated further. Second, some of the plugs in the Level 2 EVSE may have connection issues which in the context of the Tesla get exacerbated further as the Tesla outlet requires an adaptor to connect to the SAE J 1772 connector on

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the vehicle; in this case, we will have to experiment further with replacement/refinement.

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3.5.8. Demand Response Capability Limitation

Due to above issues, Tesla has limited support for Demand Response (DR) signals, which are broadcast by utility control center may request engaged vehicles to curtail the power consumption or stop charging for a pre-defined time range. Once DR signals finished, power consumption should be restored to original levels which involves commands to start charging, stop charging and modify duty-cycle for a charging session. The foreseeable mal-functions are: 1) incorrect value of power consumption; 2) not responsive to DR signals after a limited times. The issue of restoring original power consumption level is resolved by updating Tesla's software.

3.5.9. DC V2G Capability

Tesla does not have a DC port that supports V2G bidirectional charging, which is an important aspect that EVs can support future power grid. It results from the fact that there is no DC port wired directly from the batteries, and the fact that there is no bi-directional on board inverter.

3.5.10. CHAdeMO V2G Compatibility

Currently, CHAdeMO is still the most popular solution for V2G. A lot of V2G inverters are manufactured under CHAdeMO protocol. However, Tesla does not use CHAdeMO protocol, making it inaccessible to most existing V2G facilities. Customized hardware and compatible software need to be designed in order to activate the V2G function.

4. *Research Issues on Electric Vehicles*

4.1.1. Charging Parameter Identification and Control Strategy

To integrate Tesla into a charging system that uses complex algorithms, we will need to conduct further experiments to measure the vehicle's charging parameter, so we can refine our control algorithms. The parameters to study include the following:

Current Ramp up Time (Level I & II) indicates the minimum time needed for the Tesla to initiate charging and increase the charging current to an acceptable value, currently set to 0.5A and needs further research and refinement to draw any conclusions.

Maximum number of consecutive on/off actions indicate the maximum number of times a Tesla can switch charging sessions on a Level I EVSE. In addition, we need to better understand the internal BMS mechanism, including the time interval between charging sessions. This time interval is crucial for the Tesla to assess the power source stability and properly initiate charging and requires further investigation.

Power vs Duty-cycle Diagram (Level II): A Tesla can consume as much as 6 kW with a duty cycle set to 50%, while a Chevy Volt consumes only 3 kW. This higher power consumption has potential to create an instant load peak for local distribution systems and lower the charging voltage for other EVs. We must

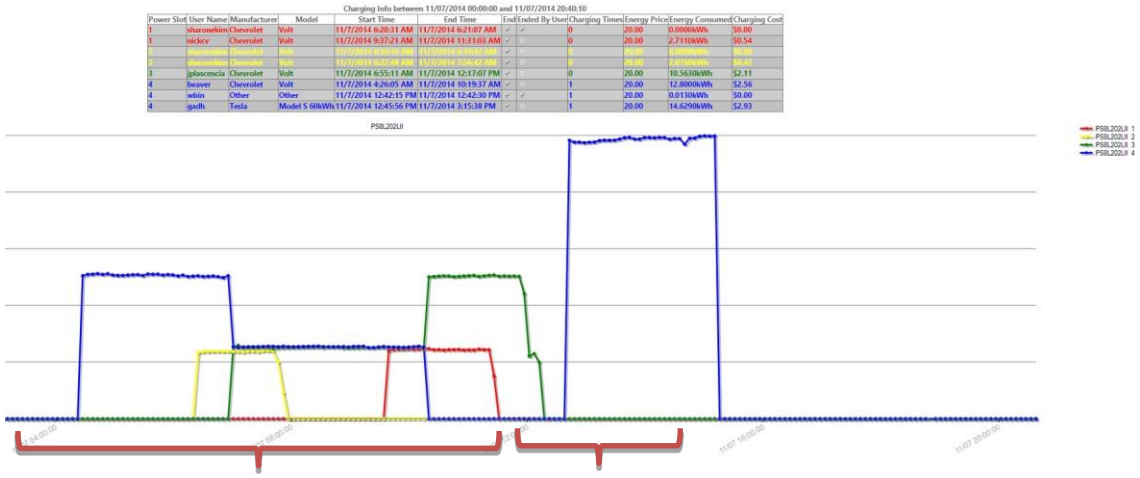
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further investigate the relation between the duty-cycle and power consumption within the Tesla's battery system in order to optimize our grid-friendly algorithms. A better understanding will also allow us to control the Tesla's power consumption by accurately setting the appropriate levels of the duty-cycle.

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shows a comparison of the power consumption between a Tesla and a Chevy Volt and this research needs further investigation.

Figure 3



Volt Tesla

Figure 3 Comparison of power consumption between Tesla and Chevy Volt

4.1.2. Pricing and Scheduling Algorithms

We must further research and design the pricing and incentive strategy design with effective server-side algorithms to take advantage of the Tesla's larger battery. Its battery has a higher power consumption capability (60 kWh / 85 kWh) than other EV types, which can potentially make it a more effective mobile energy storage device for providing regulation and aggregation services. This is being investigated currently.

The service role of energy aggregator entails optimizing the local power grid by encouraging EV users to participate, using monetary regulation signals and other incentives. However, the regulation price signal is proportional to the available capacity to provide the regulation service. The Tesla has a probability of having a higher capacity remaining for the State of Charge (SoC), which makes it possible to change power consumption on a wider range and results in added complexity for the optimization problem within our algorithms. To compensate, we must add to the existing aggregator model the following components: the parameters that indicate monetary regulation services, EV users' preferences, and responsive coefficient (elastic matrix) – these are all topics for research in the next two years.

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4.1.3. Start Debugging Issues Affecting other EVs

Since the start of the EV project, we have detected and typically resolved problem classes affecting individual EV models. For instance, the Toyota Prius had a particular type of problem when connected to a Level 1 EVSE in Parking Structure 9. We investigated this problem and other similar ones identified, and discovered that they were caused by the EV's setting, such as the timer not being closed, while others were caused by the EV's Level 1 adapter. We have been documenting such cases as they have arisen. We are now planning to actively survey our system's EV users to identify issues affecting EV classes including

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the Tesla, so we can analyze issues and solve them. Finding and debugging classes of problems that affect the Tesla constitute the next step in this research.

5. Conclusion

Bases on the data collected and user's observation, Nissan Leaf has most compatible J1772 pilot signal communication schema. Various challenges have been observed and identified through the duration of this project. However, Nissan Leaf's battery also has the most battery degradation rate among the grant vehicles.

In UCLA Campus, Nissan Leaf and Chevy Volt are still two of the most popular vehicles while Tesla Mode S 70 kWh has most energy per session.

UCLA SMERC team will continue to collect data and conduct further analysis toward the end of this project.

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Appendix AP EV Use Case 9

Technology Performance Report (TPR)
Use Case (Demonstration) #9
June 25, 2016

Demo/Use Case Name: Inductive Charging

Brief Description:

The purpose of this use case was to demonstrate the use of inductive coupling between the charging station and EV. Additional data associated with inductive charging was collected.

Design Document Methodology (anticipated in 2011)

Assumptions

The LADWP EV team procured an inductive charger and an inductive charging electric vehicle for the purposes of this use case. After installing the inductive charger and a meter to collect data, the electric vehicle was assigned to a driver in order to simulate a user with an electric vehicle and the LADWP EV team gathered charging data from the meter along with EV data from FleetCarma. Additionally, the UCLA EV team researched the theory behind inductive charging.

Demo responsibilities

This demonstration will retrofit selected EVs with adaptors and circuits to support inductive charging. Where feasible, inductive charging stations will be purchased and installed in selected areas for monitoring power consumption and usage patterns. In addition to performing the same demonstrations as other plug-in charging stations, the inductive charging demonstration will collect additional information to evaluate safety issues, convenience of usage, charging efficiency, effect of improper aligned coil, and temperature change on the coils.
Inductive charging uses an electromagnetic field (EMF) to transfer energy between two inductive coupling coils; one coil attached to the charger and the other coil attached to the EV's battery. There is a small gap between the two coils; energy is induced from one coil to the other (inductive charging does not require physical contact between the coils during the charging process). Inductive charging has a lower risk of electrical shock when compared with conductive charging because no direct contact with the cables is necessary by the EV operator. This is also particularly important in an uncovered parking area during a raining day or during cold weather when a charging cable will be stiff and hard to handle. Some disadvantages of inductive charging are its lower efficiency and increased resistive heating in comparison to conductive charging. Additional adaptors and circuits will need to be added to the EV to enable inductive charging, thereby increasing the weight of the vehicle.
The initiating event in this demonstration will be when an inductive-retrofitted EV approaches the inductive charging station and is recognized by the charging station. The EV Project team will make attempts to interface with the inductive charging stations to collect charger data such as power consumption, status of charge, charger ID, coil temperature, and other EV data for analysis. This data will be integrated with the data collected from other

chargers so that SG EV Control Center can monitor all chargers installed during this project. Demonstration success is based on the successful monitoring and controlling of the inductive charging operation and collection of all required data.

Demo steps and flow

1. Charging Station records EV Vitals
2. Charging Station records Scenario Data
3. Charging Station records Inductive Charging Data
4. EV Vitals, Scenario, & Inductive Charging Data sent to Control Center
5. Control Center sends commands to Charging Station
6. Charging Station charges EV per commands
7. On a periodic basis, Charging Station will report to Control Center status and accumulative inductive charging station data
8. EV informs Station charging is complete
   Charging Station reports results of charge to Control Center
9. Charging Station inform operator results of charging session
10. Charging Station resets for new charging session

Planned approach

44. Monitor and Evaluate Data from inductive charger
45. Document and report on Inductive Chargers

Final Used Methodology

Key changes in Demo design and justification

Because the UCLA EV team was unable to procure an inductive charger and an inductive charging capable electric vehicle, the UCLA EV team was unable to send commands to control the inductive charger. However, the LADWP EV team procured and installed an inductive charger and inductive charging capable electric vehicle and was able to gather data for this Use Case.

Technologies Deployed

List of systems/equipment deployment

- AMI Meter
- EvaTran Inductive Charger
- FleetCarma
- Modified Nissan Leaf

Success Criteria

Description of success criteria for this Demo

- To conduct the work activities outlined under the "**Demo steps and flow**"

Progress vs. success criteria

1. Charging Station records EV Vitals – **Complete**
2. Charging Station records Scenario Data – **Complete**
3. Charging Station records Inductive Charging Data – **Complete**
4. EV Vitals, Scenario, & Inductive Charging Data sent to Control Center – **Complete**
5. Control Center sends commands to Charging Station – **Not Done**
6. Charging Station charges EV per commands – **Not Done**
7. On a periodic basis, Charging Station will report to Control Center status and accumulative inductive charging station data – **Complete**
8. EV informs Station charging is complete – **Not Done**
   Charging Station reports results of charge to Control Center – **Complete**
9. Charging Station inform operator results of charging session – **Not Done**
10. Charging Station resets for new charging session – **Not Done**

Observations and Results

Observations and Results

Since there was no need to plug-in a cable, most EV drivers might feel that it may be safer to operate during a snowy or rainy weather. However, charging efficiency might be of concern when the coils are aligned properly.

Lots of effort and technology development had been dedicated in aligning the coil to gain optimal charging result. Combining with Self Driving Car technology, inductive charging may be of interest in future EV charging development.

The other concern would be its relative high cost in installation as compare with conductive EV chargers since some infrastructural modification may be needed to fit the charging station.

Lessons Learned

- Meter installation on the inductive charger was delayed. Once installed, the LADWP EV team gathered 4 months of data.
- Due to the inductive charger's location and the charger's elevated profile, the inductive charging pad was damaged by a DWP service truck.

Best Practices

None established.

Results of Data Collection

- AMI data from the charger was collected. The data included the meter events, the meter exceptions, the timestamp, the maximum Watts, the VA-h, the W-h load profile, and the cumulative W-h total. 4 months of data was collected.
- EV trip and charge data was also collected. The trip data included the timestamp, the duration, the trip distance, the electricity consumed, the total energy consumption, the starting and ending state of charge, and the ambient temperature.

- EV charge data included the timestamp, the duration, the charging power, the charger energy, the charger losses, the starting and ending state of charge, and the latitude and longitude location.

Data Collection Summary

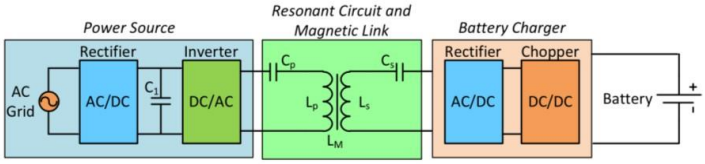


Figure 1: Inductive Charging System

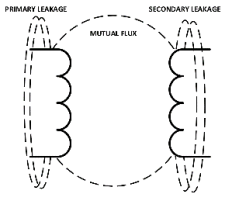


Figure 2: Primary and Secondary Coils



Figure 3: PlugLess System

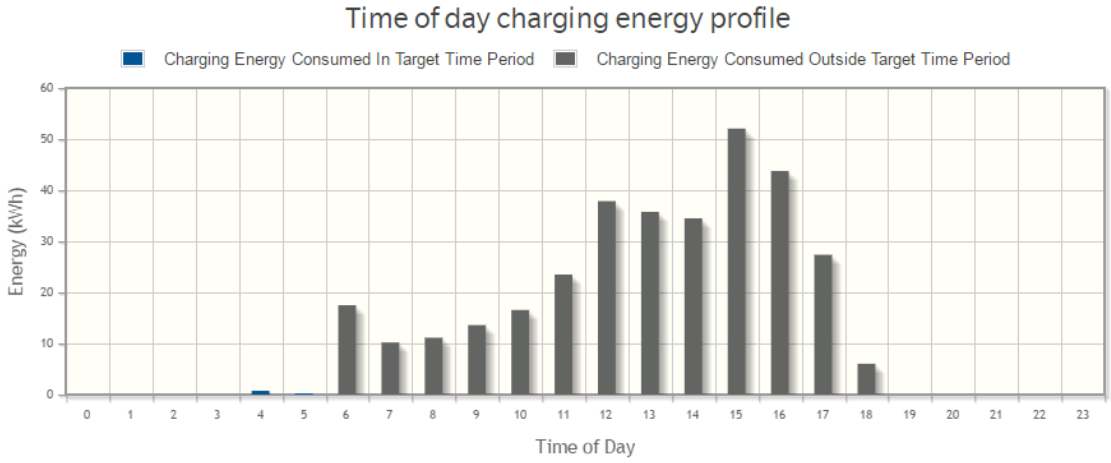


Figure 4: Time of Day Charging Energy Profile

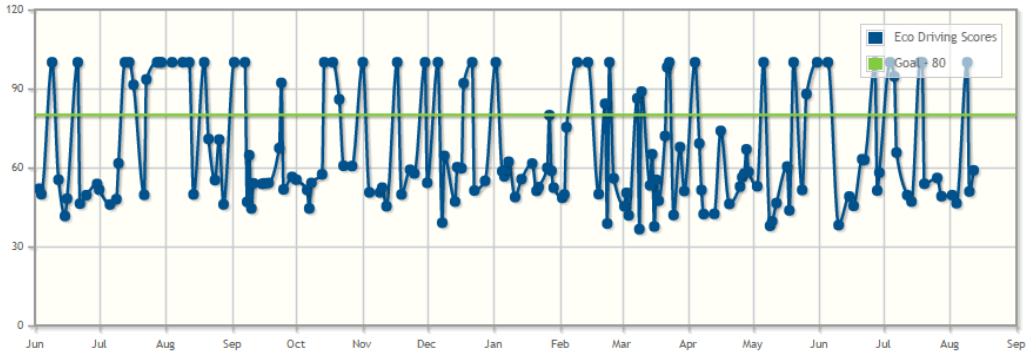


Figure 5: Daily Driver ECO Score

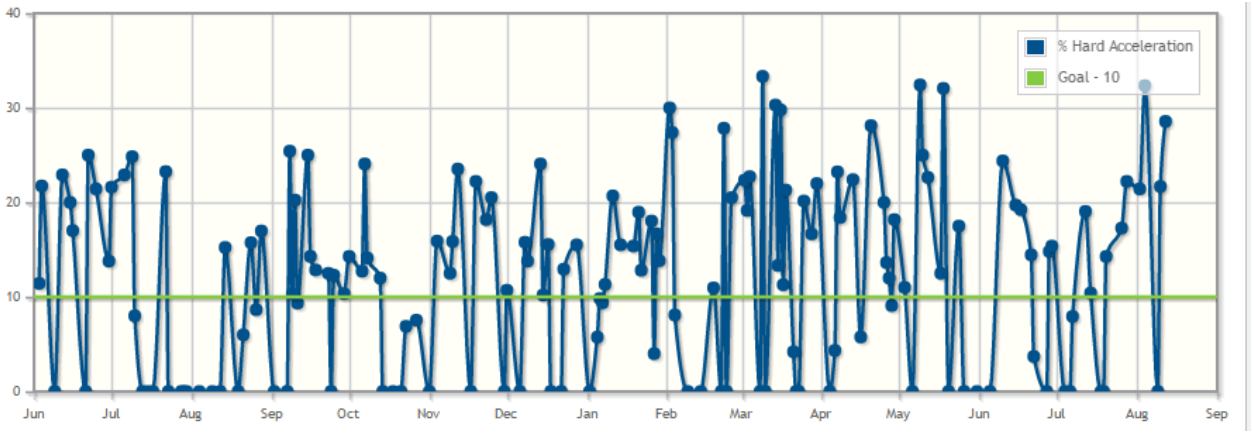


Figure 6: Daily Driver Hard Acceleration

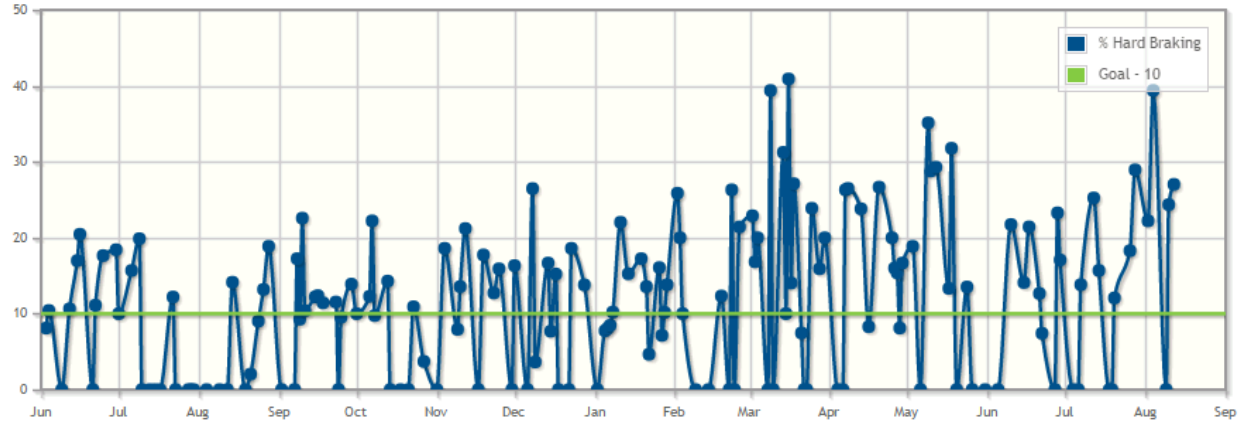


Figure 7: Daily Driver Hard Brake

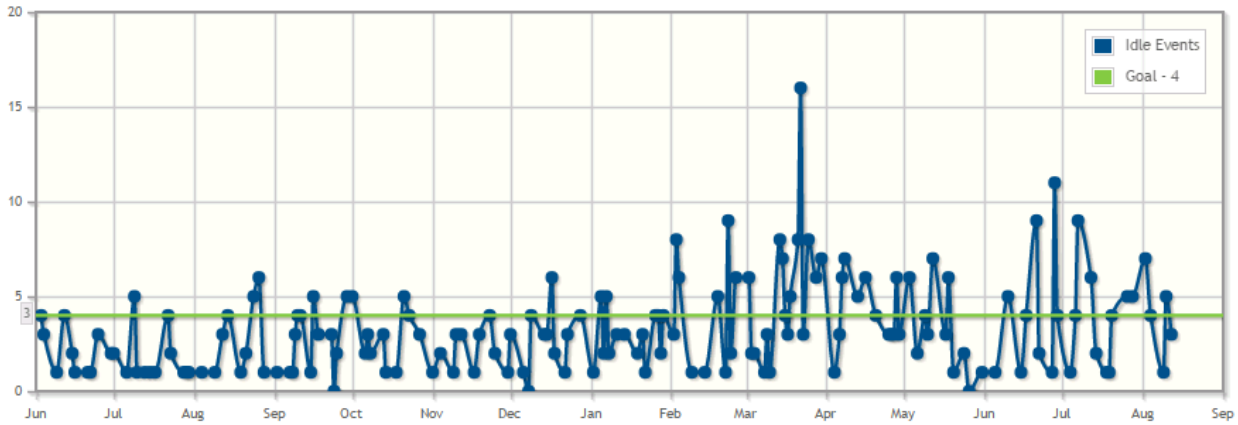


Figure 8: Daily Idle Events

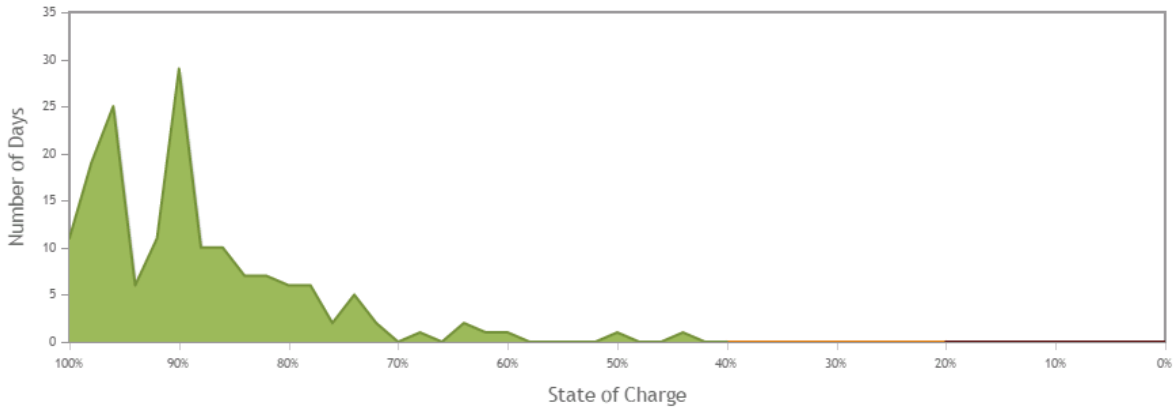


Figure 9: Histogram of Start State of Charge

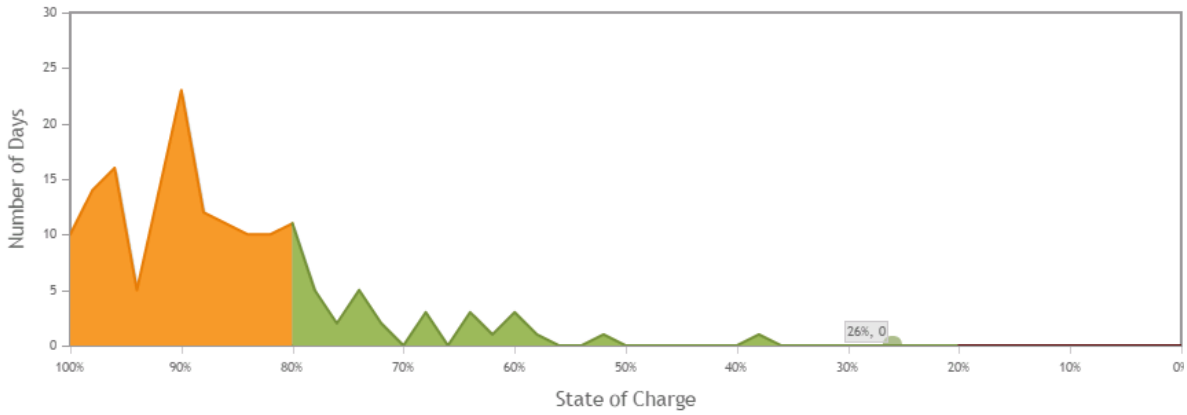


Figure 10: Histogram of End State of Charge

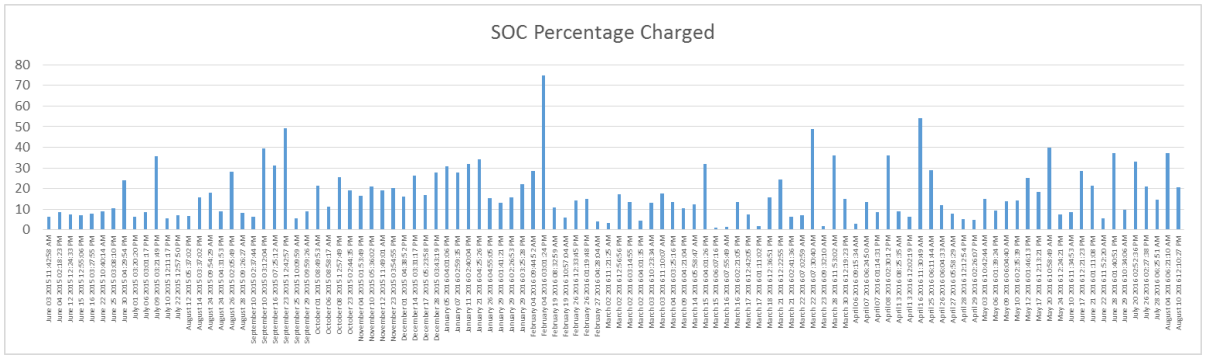


Figure 11: State of Charge Percentage Charged

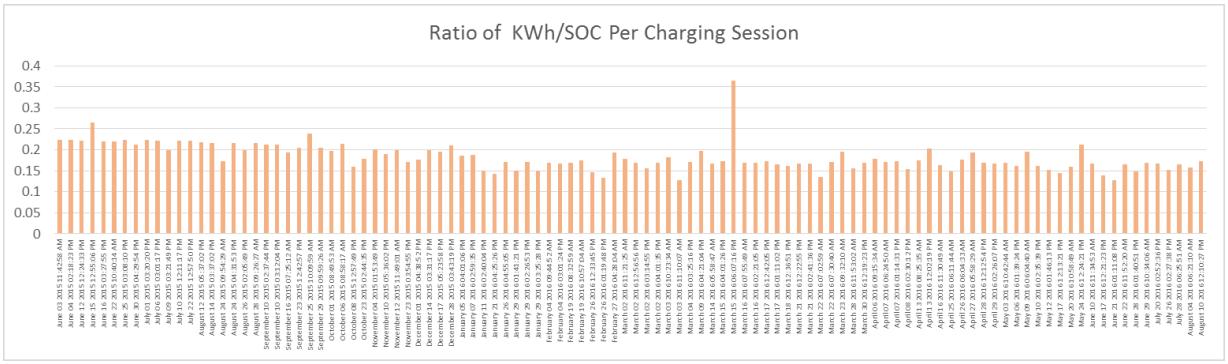


Figure 12: Ratio of kWh/State of Charge per Charging Station

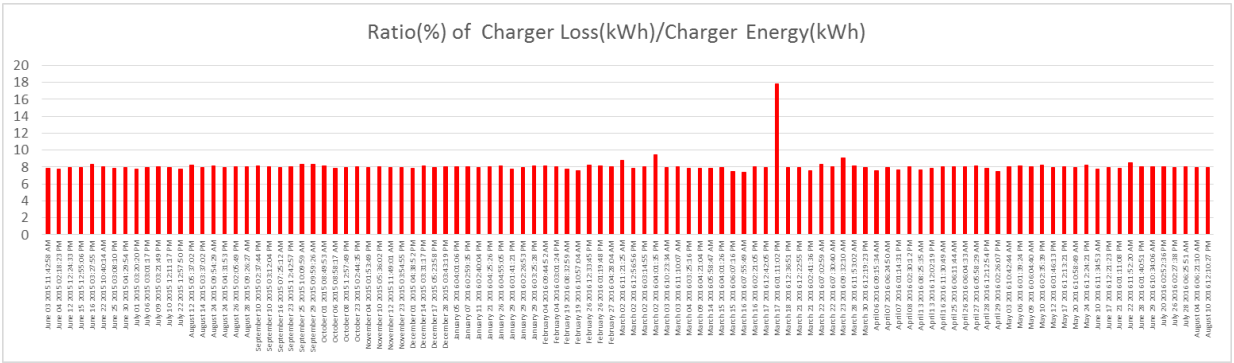


Figure 13: Ratio of Charger Loss / Charger Energy

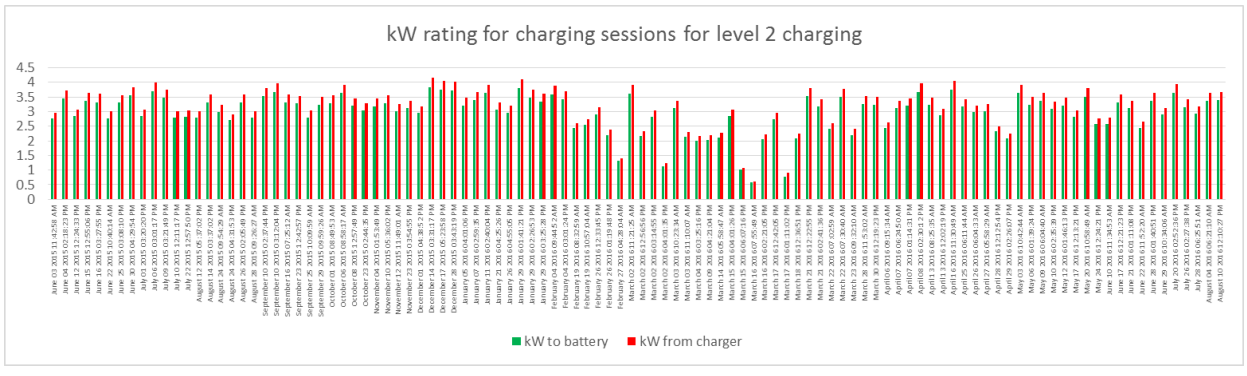


Figure 14: Average kW for each Charging Sessions with Level 2 Chargers

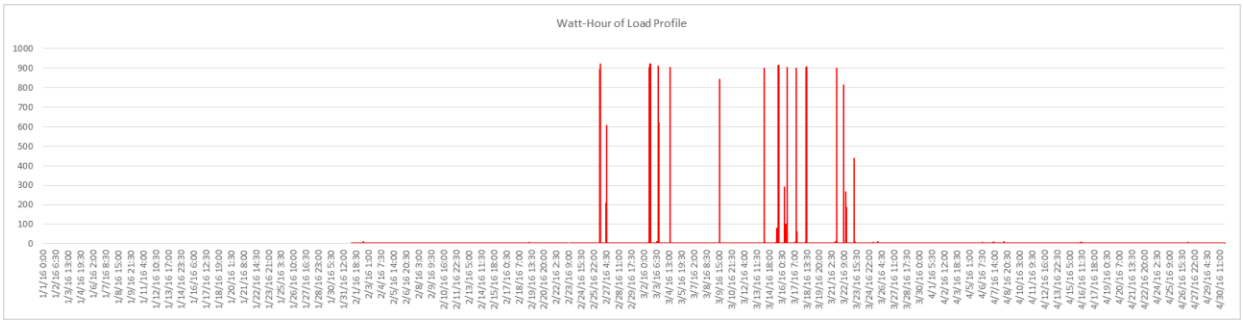


Figure 15: Watt-Hour Load Profile for Jan 01 2016 – Apr 30 2016

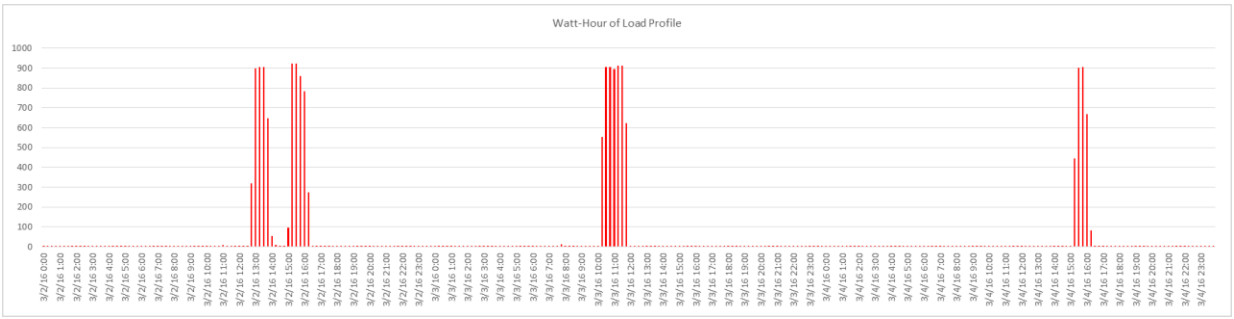


Figure 16: Watt-Hour Load Profile for Mar 02 2016 – Mar 04 2016

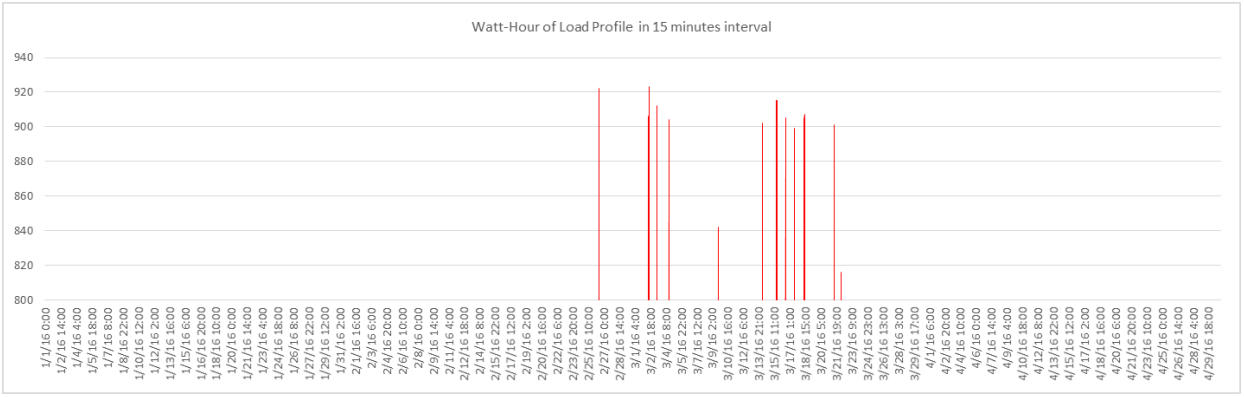


Figure 17: Watt-Hour Load Profile for Jan 01 2016 – Apr 30 2016

Charge Session Id	Start Date	Duration	Charging Power	Charger Energy (kWh)	Charger Loss (kWh)	Start SOC (%)	End SOC (%)	energy / loss energy	charged soc	kWh /Soc	Duration of charge (sec.)	kw	kw with loss
54	March 02 2016 12:56:56 PM	1:20:59	Level 2	2.92	0.23	78.9	96.3	7.876712	17.4	0.168	4859	2.163	2.334
55	March 02 2016 03:14:55 PM	0:44:59	Level 2	2.11	0.17	79.1	92.7	8.056872	13.6	0.155	2699	2.814	3.041
56	March 02 2016 04:01:35 PM	0:39:29	Level 2	0.74	0.07	92.7	97.1	9.459459	4.4	0.168	2369	1.125	1.231

Table 1: FleetCarma Data on Mar 02 2016

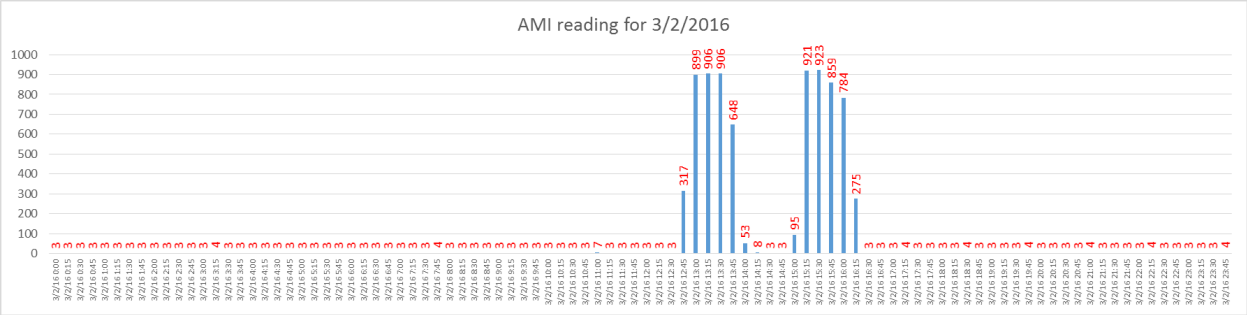


Figure 18: AMI Data for Mar 02 2016

Charge Session Id	Start Date	Duration	Charging Power	Charger Energy (kWh)	Duration of charge (min.)
54	March 02 2016 12:45:00 PM	1:30:00	Level 2	3.42	90
55	March 02 2016 03:15:00 PM	0:45:00	Level 2	2.56	45
56	March 02 2016 04:00:00 PM	0:45:00	Level 2	.28	45

Table 2: Equivalent AMI Readings for Table 1

List of Reports Published under this Demo

None established.

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Appendix AQ EV Use Case #20

Technology Performance Report (TPR)
Use Case (Demonstration) #20
August 20, 2016

Demo/Use Case Name: Generation, Transmission, and Distribution Effects

Brief Description:

With the help of the Los Angeles Department of Water and Power's Integrated Resource Planning (IRP) group, the USC EV team analyzed the electric vehicles' effects on generation, transmission, and distribution for the present and future. Additionally, the USC EV team analyzed the economic benefits of renewables on the grid alongside with electric vehicles.

Design Document Methodology

Assumptions

Gathering information performed on other Use Cases, the USC EV team researched the electric vehicles' effects on the generation, transmission, and distribution system. Additionally, the USC EV team received information on the 2014 Load Forecast from the LADWP Integrated Resource Planning group to perform production simulation case studies to assess the cost and emission impact differences of the various EV load profiles and study methodologies.

Demo responsibilities

The USC EV team studied the effects of EVs on the generation, transmission, and distribution systems under low, medium and heavy EV charging load scenarios. The study calculation was based on discrete calendar years or a total of 8,760 hours. Analysis investigated reductions in equipment loading and circuit losses, as well as the economic benefits of load balancing and peak-shaving/load-leveling. The analysis was performed and the results were reported for this demonstration.

Additionally, the USC EV team studied the use of solar energy to supply power to the EV chargers and to the grid. The solar energy would be used in the daytime to either charge EVs, charge Community Energy Storage centers, or supply energy to the grid. The team studied power quality and system reliability issues associated with introducing these renewable energy resources into the distribution grid coupled with large-scale implementation of EV chargers.

Demo steps and flow

1. Run Use Case 14 and 16 for more than 1 year to collect enough data to analyze and report results
2. Review Charging Station usage data and EV usage data by time series
3. Review any anomalies and report

Planned approach

46. Evaluate Data from LADWP IRP group and previous Use Cases
47. Document and report on Generation, Transmission, and Distribution Effects

Final Used Methodology

Key changes in Demo design and justification

In addition to collecting data from Use Case 14 and 16, the USC EV team analyzed the data collected from Use Cases 8, 11, 18, and 19 for the EVs effects on generation, transmission, and distribution. The USC EV team also received the 2014 Load Forecast information from the LADWP IRP group for the next 24 years. Additionally, due to time constraints, the USC EV team was able to complete two out of the four study cases.

For the renewables effect on generation, transmission, and distribution, only photovoltaics were utilized for the use case. Due to permitting issues and time constraints, a wind turbine was not installed and the USC EV team was unable to perform any demonstrations related to the wind turbine.

Due to the changes to the demonstration design above, the demonstration steps and flow were changed to the following:

1. Run Use Cases 8, 11, 14, 16, 18, and 19 for more than 1 year to collect enough data to analyze and report results
2. Review Charging Station usage data and EV usage data by time series
3. Review any anomalies and report

Technologies Deployed

List of systems/equipment deployment

- AMI Meters
- More than 1000 EV Chargers
- FleetCarma
- More than 60 Electric Vehicles
- Solar Panels

Success Criteria

Description of success criteria for this Demo

- Conduct the work activities outlined under the "**Key changes in Demo design and justification**"

Progress vs. success criteria

1. Run Use Cases 8, 11, 14, 16, 18, and 19 for more than 1 year to collect enough data to analyze and report results **– Complete**
2. Review Charging Station usage data and EV usage data by time series **– Complete**
3. Review any anomalies and report **– Complete**

Observations and Results

Observations and Results

The economic dispatch study conducted here did not produced results that are beneficial in meeting the objectives of this study case which is to assess the effects of EV charging load manipulation has on the generation, transmission, and distribution systems. Due to time limitation, the study was not conducted according to its original plan of conducting case scenarios to test the residential, corporate, and rideshare PV charging load profiles that were obtained through actual system data. The results obtained here, which essentially test the economic issues of PV load increase, without regard to the PV charging load profile, show no difference in impact as with any other load demand increase.

Additionally, during adverse off-peak conditions, power flow analysis revealed no thermal overloads for normal, single and credible double contingency conditions. In addition, EV charging would generally reduce pre-existing high voltages conditions. On the other hand, EV discharging would aggravate high voltage situations. Post-transient voltage stability and transient stability analyses of critical contingencies shows no violations. System swings of a special stability case when additional wind generation are tripped initially followed by the subsequent loss of all EV loads, are well damped and stable. No violations of WECC transient voltage dip and transient frequency criteria were found.

During adverse on-peak conditions, the day-time EV charging during the most adverse on-peak conditions would severely aggravate the pre-existing thermal overload conditions for the single and credible double contingencies. Also as EV charging increases, grid voltage levels generally depress but still stay within the acceptable ranges. For day-time EV charging, no post-transient voltage stability violations and no transient stability violations were found at different studied levels of EV penetration. System swings of a special stability case when additional solar generation are tripped initially followed by the subsequent loss of all EV loads, are stabilized at the end of the ten-second simulation. In contrast, the day-time EV discharging would slightly relieve the thermal overload conditions and improve low grid voltage levels. Similar to the day-time charging, no post-transient voltage stability violations and no transient stability violations were found at different studied levels of EV discharging. System swings of special stability case when all the EV discharging contributions are suddenly disconnected are stabilized at the end of the ten-second simulation.

Lessons Learned

- Time constraints and permitting issues prevented the procurement and installation of a wind turbine for the demonstration. As such, wind renewable data was unavailable for this use case.

Best Practices

None established.

Results of Data Collection

- The majority of data collected came from Use Cases 8, 11, 14, 16, 18, and 19.
- The LADWP IRP group provided the 2014 Load Forecast for the next 24 years

Data Collection Summary

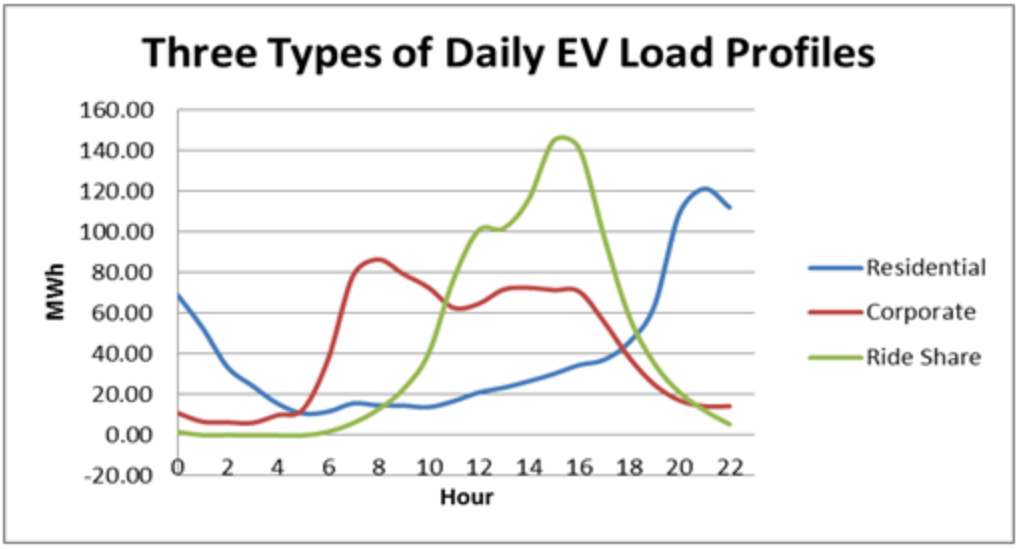


Figure 1: Three Types of EV Loads

Hour	Residenti	Corporate	Ride Share
0	69.09	10.99	1.73
1	52.84	6.71	0.10
2	33.45	6.38	0.17
3	24.28	6.16	0.00
4	15.57	9.98	0.00
5	10.76	12.70	0.00
6	11.67	37.36	1.74
7	15.69	78.62	6.01
8	14.74	86.50	12.76
9	14.66	79.36	22.70
10	13.86	72.75	40.06
11	16.82	62.75	76.71
12	21.08	64.69	100.84
13	23.42	71.77	101.79
14	26.63	72.55	116.18
15	30.21	71.47	145.04
16	34.57	70.79	141.26
17	37.17	55.83	97.78
18	45.81	38.29	58.48
19	63.44	25.01	35.35
20	109.07	17.25	21.22
21	121.32	14.32	12.28
22	112.11	14.31	5.46
23	81.72	13.45	2.35

Table 1: Data for Three Types of EV Load Profiles

Case A: Base Case NEL

Year	NEL (GWh)	PHEV (GWh)	Solar (GWh)	Wind (GWh)	NG Based (GWh)	Hydro (GWh)	Other (GWh)	Production Cost ($/MWh)	CO2 Emissions (MMT)
2016	26776	224	4097	2130	7703	835	12010	$61.64	12.62
2017	26373	270	5799	2447	7035	942	10150	$70.76	10.88
2018	26171	350	5883	2447	6671	923	10247	$74.69	10.53
2019	26072	429	5965	2447	6482	948	10230	$76.38	10.34
2020	26208	512	6045	2446	6368	948	10401	$77.71	10.41
2021	26421	592	6130	2447	6314	948	10582	$78.52	10.42
2022	26699	675	6202	2438	6600	948	10511	$78.47	10.60
2023	27031	755	7137	2766	6596	948	9584	$81.19	9.80
2024	27491	834	7088	2698	7463	915	9326	$80.21	9.50
2025	27822	897	7922	2963	10631	915	5391	$82.97	7.60
2026	28224	963	8305	3226	12923	915	2855	$84.88	6.39
2027	28615	1,018	8762	3412	12901	915	2625	$86.11	6.26
2028	29086	1,073	9411	3629	12696	915	2434	$86.40	6.18
2029	29402	1,119	9637	3627	12901	915	2321	$85.59	6.24
2030	29796	1,172	9871	3627	12875	915	2507	$85.98	6.30
2031	30201	1,220	9849	3627	12975	915	2835	$85.42	6.34
2032	30701	1,272	9829	3625	13234	915	3097	$84.73	6.45
2033	31077	1,320	9811	3627	13439	915	3285	$83.65	6.53
2034	31522	1,372	9793	3627	13665	915	3522	$84.86	6.63
2035	31978	1,424	9774	3628	14243	915	3417	$85.99	6.88

Table 2: Case A Study Results

Case B: Increased NEL

Year	NEL (GWh)	PHEV (GWh)	NEL-PHEV (GWh)	Solar (GWh)	Wind (GWh)	NG Based (GWh)	Hydro (GWh)	Other (GWh)	Production Cost ($/MWh)	CO2 Emissions (MMT)
2016	26909	357	26,552	1859	2130	7761	835	14324	$61.00	12.70
2017	26559	456	26,103	3248	2447	7103	942	12819	$70.00	11.00
2018	26420	599	25,821	3332	2447	6887	908	12847	$74.00	10.65
2019	26451	808	25,643	3414	2447	6785	918	12887	$76.00	10.53
2020	26880	1,184	25,696	3495	2446	6929	918	13092	$77.00	10.74
2021	27351	1,522	25,829	3579	2447	7073	918	13334	$77.00	10.87
2022	27741	1,717	26,024	3660	2438	7461	918	13263	$77.00	11.05
2023	28154	1,878	26,276	4267	2766	7542	918	12661	$79.00	10.30
2024	28671	2,014	26,657	4390	2698	8198	885	12500	$79.00	9.83
2025	29069	2,144	26,925	4959	2963	11758	885	8503	$81.00	8.10
2026	29528	2,267	27,261	5079	3226	14163	885	6174	$83.00	6.91
2027	29948	2,351	27,597	5350	3412	14055	885	6246	$84.00	6.73
2028	30444	2,431	28,013	5782	3629	13798	885	6349	$85.00	6.62
2029	30821	2,538	28,283	6010	3627	13830	885	6469	$85.00	6.62
2030	31271	2,647	28,624	6244	3627	13686	885	6828	$85.00	6.63
2031	31732	2,751	28,981	6222	3627	13775	885	7223	$85.00	6.66
2032	32288	2,859	29,429	6204	3625	14082	885	7491	$85.00	6.79
2033	32720	2,963	29,757	6184	3627	14330	885	7694	$84.00	6.89
2034	33221	3,071	30,150	6166	3627	14636	885	7907	$84.92	7.02
2035	33621	3,067	30,554	6146	3628	15177	885	7784	$86.36	7.25

Table 3: Case B Study Results

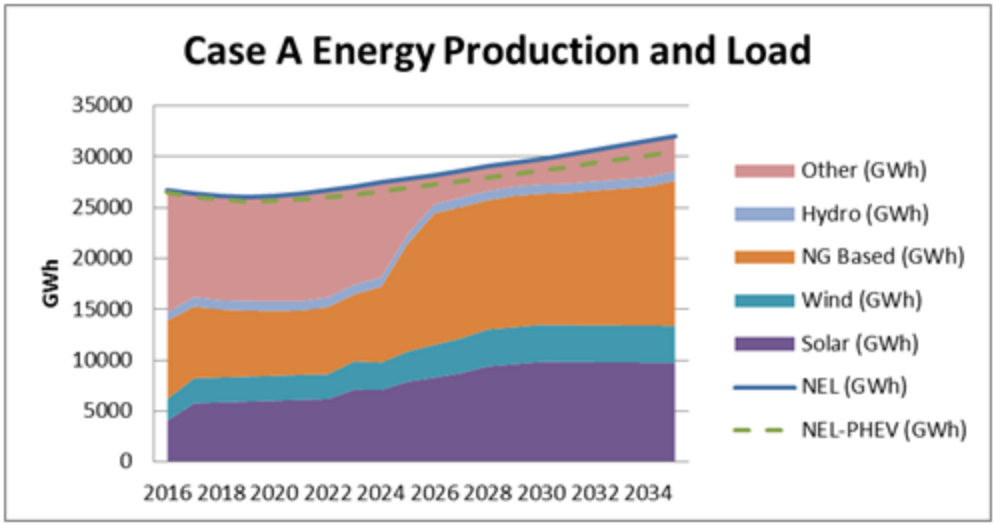


Figure 2: Case A NEL and PV Load Based on LADWP IRP Study 2014

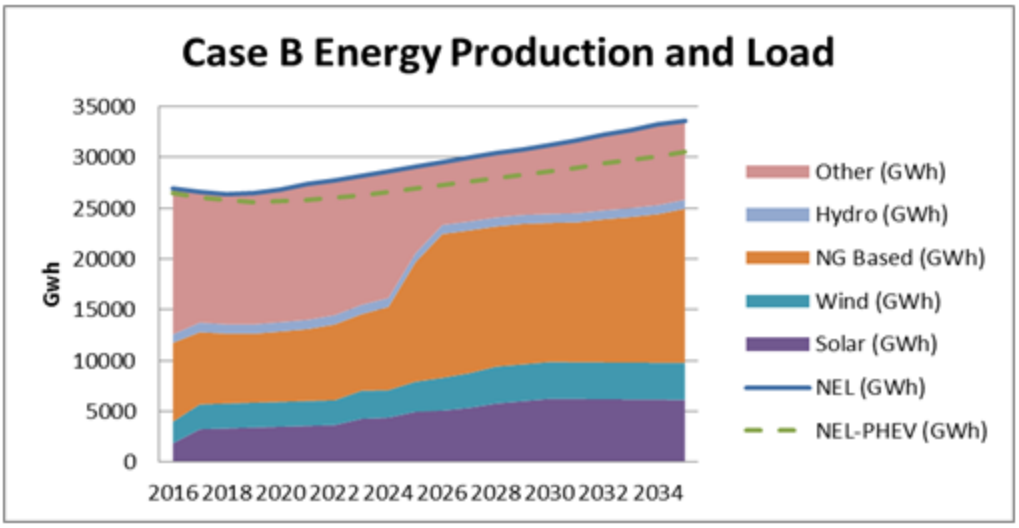


Figure 3: Case B Increase NEL by Doubling PV Penetration

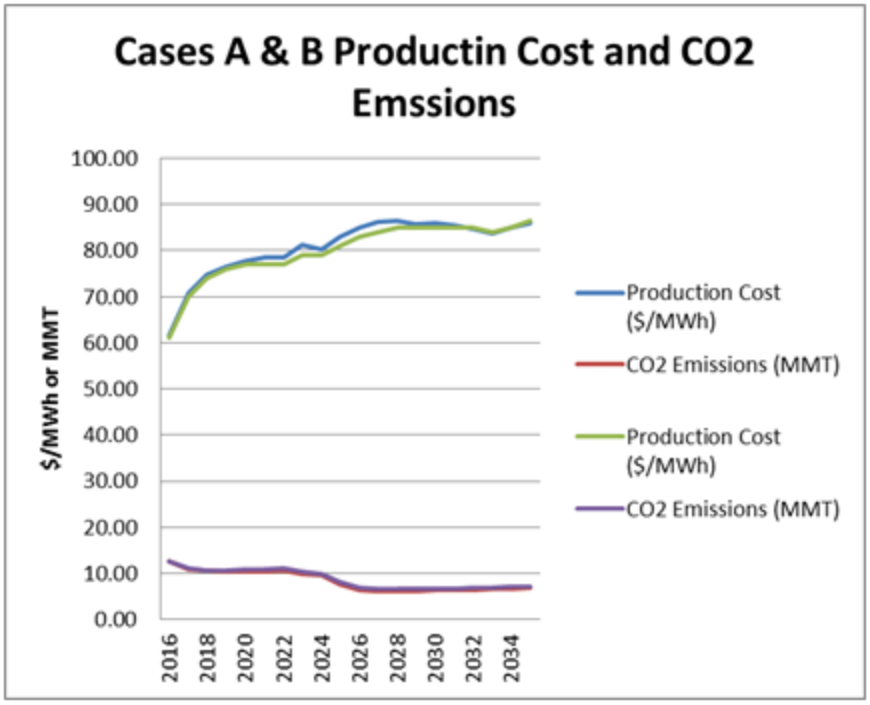


Figure 4: Case A & B Production Cost and CO2 Emission Comparison

SERVICE AREA	RECEIVING STATION		2020 LIGHT WINTER							
			G2V (Grid-to-Vehicle or Charging)							
			A0		A1 +10%		A2 & A4 +20%		A3 +30%	
			MW	Mvar	MW	Mvar	MW	Mvar	MW	Mvar
CENTRAL	RS-N	AIRPORT	109	14	120	14	131	14	142	14
	RS-G	ATWATER	104	-19	114	-19	125	-19	135	-19
	RS-B	CENTURY	135	-9	149	-9	162	-9	176	-9
	RS-D	FAIRFAX	160	-8	176	-8	192	-8	208	-8
	RS-H	HOLLYWOOD	138	1	152	1	166	1	179	1
	RS-P	MARKET (RIVER)	162	50	178	50	194	50	211	50
	RS-K	OLYMPIC	130	-11	143	-11	156	-11	169	-11
	RS-L	SCATTERGOOD	18	8	20	8	22	8	23	8
	RS-A	ST JOHN	77	30	85	30	92	30	100	30
	RS-F	VELASCO	74	15	81	15	89	15	96	15
	Total Central Load		1108	71	1218	71	1328	71	1439	71
SOUTHERN	RS-HAL	HALLDALE	19	4	21	4	23	4	25	4
	RS-Q	HARBOR	79	18	87	18	95	18	103	18
	RS-C	WILMINGTON	38	7	42	7	46	7	49	7
	Total Southern Load		136	29	150	29	163	29	177	29
VALLEY	RS-T	CANOGA	80	-12	88	-12	96	-12	104	-12
	RS-J	NORTHRIDGE	113	-19	124	-19	136	-19	147	-19
	RS-RIN	RINALDI	70	-7	77	-7	84	-7	91	-7
	RS-U	TARZANA	61	-27	67	-27	73	-27	79	-27
	RS-E	TOLUCA	101	-24	111	-24	121	-24	131	-24
	RS-M	VALLEY	71	-2	78	-2	85	-2	92	-2
	RS-S	VAN NUYS	108	-8	119	-8	130	-8	140	-8
	Total Valley Load		604	-99	664	-99	725	-99	785	-99
TOTAL RECEIVING STATION LOAD			1848	1	2032	1	2216	1	2401	1

Table 4: Total Load Forecast and EV Charging at 10%, 20%, and 30% (MW)

SERVICE AREA	RECEIVING STATION	2020 LIGHT WINTER							
		G2V (Vehicle-to-Grid or Discharging)							
		A0		A5 -10%		A6 -20%		A7 -30%	
		MW	Mvar	MW	Mvar	MW	Mvar	MW	Mvar
CENTRAL	RS-N AIRPORT	109	14	98	14	87	14	76	14
	RS-G ATWATER	104	-19	94	-19	83	-19	73	-19
	RS-B CENTURY	135	-9	122	-9	108	-9	95	-9
	RS-D FAIRFAX	160	-8	144	-8	128	-8	112	-8
	RS-H HOLLYWOOD	138	1	124	1	110	1	97	1
	RS-P MARKET (RIVER)	162	50	146	50	130	50	113	50
	RS-K OLYMPIC	130	-11	117	-11	104	-11	91	-11
	RS-L SCATTERGOOD	18	8	16	8	14	8	13	8
	RS-A ST JOHN	77	30	69	30	62	30	54	30
	RS-F VELASCO	74	15	67	15	59	15	52	15
	Total Central Load	1108	71	996	71	886	71	775	71
SOUTHERN	RS-HAL HALLDALE	19	4	17	4	15	4	13	4
	RS-Q HARBOR	79	18	71	18	63	18	55	18
	RS-C WILMINGTON	38	7	34	7	30	7	27	7
	Total Southern Load	136	29	122	29	109	29	95	29
VALLEY	RS-T CANOGA	80	-12	72	-12	64	-12	56	-12
	RS-J NORTHRIDGE	113	-19	102	-19	90	-19	79	-19
	RS-RIN RINALDI	70	-7	63	-7	56	-7	49	-7
	RS-U TARZANA	61	-27	55	-27	49	-27	43	-27
	RS-E TOLUCA	101	-24	91	-24	81	-24	71	-24
	RS-M VALLEY	71	-2	64	-2	57	-2	50	-2
	RS-S VAN NUYS	108	-8	97	-8	86	-8	76	-8
	Total Valley Load	604	-99	544	-99	483	-99	423	-99
TOTAL RECEIVING STATION LOAD		1848	1	1662	1	1478	1	1293	1

Table 5: Total Load Forecast and EV Discharging at 10%, 20%, and 30% (MW)

calculation	A	B	C=A+B	D	E=C+50%(D)	F	G=E-F
Year	**Net 1-in-10 Peak**	**Co-Generation**	**Gross 1-in-10**	**Energy Efficiency**	**Adjusted 1-in-10 Peak**	**OV & Losses**	**Coincident Peak**
2014	6102	243	6345	58	6374	522	5852
2015	6058	248	6306	79	6346	531	5815
2016	6007	252	6259	99	6309	539	5770
2017	5968	254	6222	116	6280	546	5734
2018	5958	256	6214	131	6280	553	5727
2019	5956	258	6214	144	6286	560	5726
2020	5955	261	6216	155	6294	568	5726
2021	6031	264	6295	166	6378	576	5802

Table 6: Coincident Peak Load Forecast (MW)

SERVICE	RECEIVING STATION	2020 HEAVY SUMMER

AREA			G2V (EV Charging)							
			B0		B1 +2.5%		B2 +5%		B3 AND B4 + 10%	
			MW	Mvar	MW	Mvar	MW	Mvar	MW	Mvar
CENTRAL	RS-N	AIRPORT	200	63	205	63	210	63	220	63
	RS-G	ATWATER	304	68	312	68	319	68	334	68
	RS-B	CENTURY	293	72	300	72	308	72	322	72
	RS-D	FAIRFAX	374	92	383	92	393	92	411	92
	RS-H	HOLLYWOOD MARKET	388	74	398	74	407	74	427	74
	RS-P	(RIVER)	343	53	352	53	360	53	377	53
	RS-K	OLYMPIC	405	117	415	117	425	117	446	117
	RS-L	SCATTERGOOD	25	12	26	12	26	12	28	12
	RS-A	ST JOHN	214	49	219	49	225	49	235	49
	RS-F	VELASCO	214	47	219	47	225	47	235	47
	Total Central Load		2760	647	2829	647	2898	647	3036	647
SOUTHERN	RS-HAL	HALLDALE	47	17	48	17	49	17	52	17
	RS-Q	HARBOR	191	58	196	58	201	58	210	58
	RS-C	WILMINGTON	155	19	159	19	163	19	171	19
	Total Southern Load		393	94	403	94	413	94	432	94
VALLEY	RS-T	CANOGA	338	62	346	62	355	62	372	62
	RS-J	NORTHRIDGE	527	99	540	99	553	99	580	99
	RS-RIN	RINALDI	288	71	295	71	302	71	317	71
	RS-U	TARZANA	331	25	339	25	348	25	364	25
	RS-E	TOLUCA	381	79	391	79	400	79	419	79
	RS-M	VALLEY	298	86	305	86	313	86	328	86
	RS-S	VAN NUYS	411	26	421	26	432	26	452	26
	Total Valley Load		2574	448	2638	448	2703	448	2831	448
TOTAL RECEIVING STATION LOAD			5727	1189	5870	1189	6013	1189	6300	1189

Table 7: Total Load Forecast and EV Charging at 2.5%, 5%, and 10% (MW)

SERVICE AREA	RECEIVING STATION		2020 HEAVY SUMMER							
			G2V		V2G (EV Discharging)					
			B0		B5-2.5%		B6 -5%		B7 -10%	
			MW	Mvar	MW	Mvar	MW	Mvar	MW	Mvar
CENTRAL	RS-N	AIRPORT	200	63	195	63	190	63	180	63
	RS-G	ATWATER	304	68	296	68	289	68	274	68
	RS-B	CENTURY	293	72	286	72	278	72	264	72
	RS-D	FAIRFAX	374	92	365	92	355	92	337	92
	RS-H	HOLLYWOOD MARKET	388	74	378	74	369	74	349	74
	RS-P	(RIVER)	343	53	334	53	326	53	309	53
	RS-K	OLYMPIC	405	117	395	117	385	117	365	117

	RS-L	SCATTERGOOD	25	12	24	12	24	12	23	12
	RS-A	ST JOHN	214	49	209	49	203	49	193	49
	RS-F	VELASCO	214	47	209	47	203	47	193	47
	Total Central Load		2760	647	2691	647	2622	647	2484	647
SOUTHERN	RS-HAL	HALLDALE	47	17	46	17	45	17	42	17
	RS-Q	HARBOR	191	58	186	58	181	58	172	58
	RS-C	WILMINGTON	155	19	151	19	147	19	140	19
	Total Southern Load		393	94	383	94	373	94	354	94
VALLEY	RS-T	CANOGA	338	62	330	62	321	62	304	62
	RS-J	NORTHRIDGE	527	99	514	99	501	99	474	99
	RS-RIN	RINALDI	288	71	281	71	274	71	259	71
	RS-U	TARZANA	331	25	323	25	314	25	298	25
	RS-E	TOLUCA	381	79	371	79	362	79	343	79
	RS-M	VALLEY	298	86	291	86	283	86	268	86
	RS-S	VAN NUYS	411	26	401	26	390	26	370	26
	Total Valley Load		2574	448	2510	448	2445	448	2317	448
TOTAL RECEIVING STATION LOAD			5727	1189	5584	1189	5441	1189	5154	1189

Table 8: Total Load Forecast and EV Discharging at 2.5%, 5%, and 10% (MW)

Resource Type	2020 Capacity (MW)	2020 Heavy Summer	2020 Light Winter
Pumped Storage	1247	93	(388)
Natural Gas	3638	1216	0
Wind	244	27	40
Solar	528.5	303	0
Hydroelectric	177	30	50
Internal Generation	***5834.5***	***1669***	***90***
% of Total Generation	64%	36%	4%
Hydroelectric	495	400	400
Wind	388	70	297
Solar	460	460	0
Coal	1092	1092	1092
Nuclear	387	387	387
Natural Gas	500	500	174
External Generation	***3322***	***2909***	***2350***
% of Total Generation	36%	64%	96%
Total Generation	**9156.5**	**4578**	**2440**

Table 9: Generation Mix Assumed for Base Cases A0 and B0

		A0-LWBase			A1-5%G2V			A2-10%G2V			A3-30%G2V		
BUS #	NAME	KV	V-PU	KV	V-PU	kV	Delta (kV)	V-PU	kV	Delta (kV)	V-PU	kV	Delta (kV)
26013	AIRWAY	230	1.0422	239.7	1.0404	239.3	-0.4	1.0385	238.9	-0.9	1.0361	238.3	-1.4
26025	HAYNES	230	1.03	236.9	1.0436	240.0	3.1	1.0408	239.4	2.5	1.0374	238.6	1.7
26286	HAY N	230	1.03	236.9	1.0417	239.6	2.7	1.0386	238.9	2.0	1.0349	238.0	1.1
26052	OLIVE	230	1.0443	240.2	1.0417	239.6	-0.6	1.0386	238.9	-1.3	1.0349	238.0	-2.2
26061	RINALDI	230	1.0443	240.2	1.0417	239.6	-0.6	1.0386	238.9	-1.3	1.0349	238.0	-2.2
26063	RIVER	230	1.0369	238.5	1.0278	236.4	-2.1	1.0259	236.0	-2.5	1.0235	235.4	-3.1
26066	SCATERGD	230	1.0283	236.5	1.0278	236.4	-0.1	1.0259	236.0	-0.6	1.0235	235.4	-1.1
26068	STJOHN	230	1.0371	238.5	1.0441	240.1	1.6	1.0437	240.1	1.5	1.0421	239.7	1.2
26072	CNTURYLD	230	1.0412	239.5	1.0437	240.1	0.6	1.0427	239.8	0.3	1.0411	239.5	0.0
26078	TOLUCA	230	1.0449	240.3	1.0346	238.0	-2.4	1.0322	237.4	-2.9	1.0293	236.7	-3.6
26268	TOL E	230	1.0449	240.3	1.0378	238.7	-1.6	1.0357	238.2	-2.1	1.0328	237.5	-2.8
26080	VELASCO	230	1.0382	238.8	1.0267	236.1	-2.6	1.0248	235.7	-3.1	1.0224	235.2	-3.6
26081	ATWATER	230	1.0408	239.4	1.0348	238.0	-1.4	1.0325	237.5	-1.9	1.0297	236.8	-2.6
26086	NRTHRDGE	230	1.0446	240.3	1.0425	239.8	-0.5	1.0398	239.2	-1.1	1.0365	238.4	-1.9
26087	OLYMPC	230	1.0343	237.9	1.0387	238.9	1.0	1.0361	238.3	0.4	1.0329	237.6	-0.3
26093	TARZANA	230	1.0445	240.2	1.0412	239.5	-0.8	1.038	238.7	-1.5	1.0342	237.9	-2.4
26094	SYLMARLA	230	1.0457	240.5	1.0374	238.6	-1.9	1.0341	237.8	-2.7	1.0302	236.9	-3.6
26103	VALLEY	230	1.0446	240.3	1.0313	237.2	-3.1	1.0289	236.6	-3.6	1.0258	235.9	-4.3
26014	GRAMERC1	138	1.0462	144.4	1.0395	143.5	-0.9	1.0376	143.2	-1.2	1.035	142.8	-1.5
26016	HALLDALE-W	138	1.0446	144.2	1.0433	144.0	-0.2	1.0414	143.7	-0.4	1.039	143.4	-0.8
26260	HALLDALE-C	138	1.0446	144.2	1.0433	144.0	-0.2	1.0414	143.7	-0.4	1.039	143.4	-0.8
26261	HALLDALE-E	138	1.0446	144.2	1.0359	143.0	-1.2	1.0335	142.6	-1.5	1.0305	142.2	-1.9
26065	SCATERGD	138	1.0398	143.5	1.0389	143.4	-0.1	1.0368	143.1	-0.4	1.0342	142.7	-0.8
26069	CNTURY	138	1.0451	144.2	1.0323	142.5	-1.8	1.03	142.1	-2.1	1.0269	141.7	-2.5
26073	WLMNTN	138	1.0443	144.1	1.0323	142.5	-1.7	1.03	142.1	-2.0	1.0269	141.7	-2.4
26075	WLMNTNLD	138	1.0406	143.6	1.0344	142.7	-0.9	1.0323	142.5	-1.1	1.0296	142.1	-1.5
26076	FAIRFAX	138	1.0334	142.6	1.044	144.1	1.5	1.0431	143.9	1.3	1.0413	143.7	1.1
26077	TOLUCA	138	1.0413	143.7	1.0326	142.5	-1.2	1.0308	142.3	-1.4	1.0281	141.9	-1.8
26083	HOLYWD1	138	1.0344	142.7	1.0374	143.2	0.4	1.0354	142.9	0.1	1.0326	142.5	-0.2
26084	HOLYWD2	138	1.0344	142.7	1.0325	142.5	-0.3	1.0302	142.2	-0.6	1.0271	141.7	-1.0
26085	HOLYWDLD	138	1.0363	143.0	1.0412	143.7	0.7	1.038	143.2	0.2	1.0342	142.7	-0.3
26088	OLYMPCLD	138	1.0392	143.4	1.0406	143.6	0.2	1.0388	143.4	-0.1	1.0363	143.0	-0.4
26089	AIRPORT	138	1.0346	142.8	1.0435	144.0	1.2	1.0422	143.8	1.0	1.0401	143.5	0.8
26091	HARBOR	138	1.0443	144.1	1.0451	144.2	0.1	1.0443	144.1	0.0	1.0429	143.9	-0.2
26092	TARZANA	138	1.042	143.8	1.0419	143.8	0.0	1.0389	143.4	-0.4	1.0352	142.9	-0.9
26095	TAP 1	138	1.0448	144.2	1.0419	143.8	-0.4	1.0389	143.4	-0.8	1.0352	142.9	-1.3
26096	TAP 2	138	1.0448	144.2	1.0433	144.0	-0.2	1.0418	143.8	-0.4	1.0398	143.5	-0.7
26102	VALLEY	138	1.0445	144.1	1.0434	144.0	-0.2	1.042	143.8	-0.3	1.0399	143.5	-0.6
	Average						-0.4			-0.8			-1.3

Table 10: Overvoltage Improvement at Various EV Charging Levels

		A0-LWBase			A5-10%V2G			A6-10%V2G			A7-30%V2G		
BUS #	NAME	KV	V-PU	KV	V-PU	kV	Delta (kV)	V-PU	kV	Delta (kV)	V-PU	kV	Delta (kV)
26013	AIRWAY	230	1.0422	239.7	1.0437	240.1	0.3	1.0447	240.3	0.6	1.0488	241.2	1.5
26025	HAYNES	230	1.03	236.9	1.032	237.4	0.5	1.0336	237.7	0.8	1.0384	238.8	1.9
26286	HAY N	230	1.03	236.9	1.032	237.4	0.5	1.0336	237.7	0.8	1.0384	238.8	1.9
26052	OLIVE	230	1.0443	240.2	1.044	240.1	-0.1	1.0431	239.9	-0.3	1.0453	240.4	0.2
26061	RINALDI	230	1.0443	240.2	1.0447	240.3	0.1	1.0447	240.3	0.1	1.0477	241.0	0.8
26063	RIVER	230	1.0369	238.5	1.039	239.0	0.5	1.0406	239.3	0.9	1.0454	240.4	2.0
26066	SCATERGD	230	1.0283	236.5	1.0295	236.8	0.3	1.0304	237.0	0.5	1.0334	237.7	1.2
26068	STJOHN	230	1.0371	238.5	1.0391	239.0	0.5	1.0406	239.3	0.8	1.0453	240.4	1.9
26072	CNTURYLD	230	1.0412	239.5	1.0435	240.0	0.5	1.0453	240.4	0.9	1.0504	241.6	2.1
26078	TOLUCA	230	1.0449	240.3	1.0462	240.6	0.3	1.0472	240.9	0.5	1.0514	241.8	1.5
26268	TOL E	230	1.0449	240.3	1.0462	240.6	0.3	1.0472	240.9	0.5	1.0514	241.8	1.5
26080	VELASCO	230	1.0382	238.8	1.0403	239.3	0.5	1.042	239.7	0.9	1.0469	240.8	2.0
26081	ATWATER	230	1.0408	239.4	1.0425	239.8	0.4	1.0438	240.1	0.7	1.0481	241.1	1.7
26086	NRTHRDGE	230	1.0446	240.3	1.0448	240.3	0.0	1.0445	240.2	0.0	1.0471	240.8	0.6
26087	OLYMPC	230	1.0343	237.9	1.0355	238.2	0.3	1.0364	238.4	0.5	1.0396	239.1	1.2
26093	TARZANA	230	1.0445	240.2	1.045	240.4	0.1	1.0451	240.4	0.1	1.0481	241.1	0.8
26094	SYLMARLA	230	1.0457	240.5	1.0459	240.6	0.0	1.0457	240.5	0.0	1.0484	241.1	0.6
26103	VALLEY	230	1.0446	240.3	1.0455	240.5	0.2	1.046	240.6	0.3	1.0497	241.4	1.2
26014	GRAMERC1	138	1.0462	144.4	1.0486	144.7	0.3	1.0505	145.0	0.6	1.0557	145.7	1.3
26016	HALLDALE-W	138	1.0446	144.2	1.0473	144.5	0.4	1.0494	144.8	0.7	1.055	145.6	1.4
26260	HALLDALE-C	138	1.0446	144.2	1.0473	144.5	0.4	1.0494	144.8	0.7	1.055	145.6	1.4
26261	HALLDALE-E	138	1.0446	144.2	1.0473	144.5	0.4	1.0494	144.8	0.7	1.055	145.6	1.4
26065	SCATERGD	138	1.0398	143.5	1.0413	143.7	0.2	1.0424	143.9	0.4	1.046	144.3	0.9
26069	CNTURY	138	1.0451	144.2	1.0475	144.6	0.3	1.0493	144.8	0.6	1.0546	145.5	1.3
26073	WLMNTN	138	1.0443	144.1	1.047	144.5	0.4	1.0493	144.8	0.7	1.0549	145.6	1.5
26075	WLMNTNLD	138	1.0406	143.6	1.0435	144.0	0.4	1.0458	144.3	0.7	1.0516	145.1	1.5
26076	FAIRFAX	138	1.0334	142.6	1.0352	142.9	0.2	1.0364	143.0	0.4	1.0404	143.6	1.0
26077	TOLUCA	138	1.0413	143.7	1.0427	143.9	0.2	1.0438	144.0	0.3	1.048	144.6	0.9
26083	HOLYWD1	138	1.0344	142.7	1.0361	143.0	0.2	1.0374	143.2	0.4	1.0414	143.7	1.0
26084	HOLYWD2	138	1.0344	142.7	1.0361	143.0	0.2	1.0374	143.2	0.4	1.0414	143.7	1.0
26085	HOLYWDLD	138	1.0363	143.0	1.0379	143.2	0.2	1.039	143.4	0.4	1.0434	144.0	1.0
26088	OLYMPCLD	138	1.0392	143.4	1.0406	143.6	0.2	1.0415	143.7	0.3	1.045	144.2	0.8
26089	AIRPORT	138	1.0346	142.8	1.0363	143.0	0.2	1.0375	143.2	0.4	1.0413	143.7	0.9
26091	HARBOR	138	1.0443	144.1	1.047	144.5	0.4	1.0493	144.8	0.7	1.055	145.6	1.5
26092	TARZANA	138	1.042	143.8	1.043	143.9	0.1	1.0436	144.0	0.2	1.0468	144.5	0.7
26095	TAP 1	138	1.0448	144.2	1.0475	144.6	0.4	1.0496	144.8	0.7	1.0551	145.6	1.4
26096	TAP 2	138	1.0448	144.2	1.0475	144.6	0.4	1.0496	144.8	0.7	1.0551	145.6	1.4
26102	VALLEY	138	1.0445	144.1	1.0455	144.3	0.1	1.046	144.3	0.2	1.0497	144.9	0.7
	Average						0.3			0.5			1.3

Table 11: Overvoltage Worsening at Various EV Discharging Levels

CONT.	CIRCUIT					IMPACTED ELEMENT	HEAVY SUMMER			
							B0	B1-3%G2V	B2-5%G2V	B3-10%G2V
(N-1) NERC Categories B2 and B3										
500kV Lines										
1.	26003	ADELANTO	26115	RINALDI2	1	TOLUCA 500/230 [illegible] "H"	90%	90%	91%	91%
2.	26003	ADELANTO	26079	TOLUCA	1	VALLEY - RINALDI 230kV Line 1	102%	105%	109%	116%
						VALLEY - RINALDI 230kV Line 2	102%	105%	109%	116%
						VICTORVL - VIC16-18 500/287 [illegible] "K"	99%	101%	102%	105%
						RINALDI 500/230kV [illegible] H				
17.	26051	MEAD	26266	VIC15-13	1	VICTORVL - VIC16-18 500/287 [illegible] "K"	95%	96%	97%	100%
72.	26093	TARZANA	26087	OLYMPC	3	TARZANA 230/138Kv [illegible] E		90%	95%	105%
						TARZANA-RBK JUN Cable A				100%
						TARZANA-RBK JUN Cable B				100%
89.	26069	CNTURY	26014	GRAMERCY	1	CNTURY-GRAMERCY Line 2	99%	101%	103%	107%
90.	26069	CNTURY	26014	GRAMERCY	2	CNTURY-GRAMERCY Line 1	99%	101%	103%	107%
114.	26095	TAP1	26014	GRAMERCY	1	TAP2-GRAMERCY line 1		93%	97%	104%
117.	26096	TAP2	26014	GRAMERCY	1	TAP1-GRAMERCY line 1		93%	97%	104%
146.	26093	TARZANA 230	26092	TARZANA 138	E	TARZANA-OLYMPC Ckt 3			92%	103%
(N-2) NERC Category C5										
500kV Lines										
1.	26003	ADELANTO	26115	RINALDI2	1	TOLUCA 230/500kV [illegible] "G"	111%	112%	112%	112%
						VICTORVL - VIC16-18 500/287kV [illegible] "K"	106%	107%	108%	110%
21.	26061	RINALDI	26013	AIRWAY	1	TOL E -ATWATER 230kV Line 1	93%	97%	102%	110%
	26061	RINALDI	26013	AIRWAY	2					
22.	26061	RINALDI	26093	TARZANA	1	NRTHRDGE - TARZANA 230kV Line 1	91%	95%	100%	109%
	26061	RINALDI	26093	TARZANA	2					
23.	26093	TARZANA	26087	OLYMPC	3	HOLYWD1 - HOLYWDLD 138kV Reactor	100%	104%	109%	119%
	26092	TARZANA	26088	OLYMPCLD	1	HOLYWD2 - HOLYWDLD 138kV Reactor	100%	104%	109%	119%
Common Breaker Mode of Failure NERC Category C2										
500kV Lines										
1.	26003	ADELANTO	26115	RINALDI2	1	TOLUCA 500/230kV [illegible] "H"	92%	92%	92%	93%
	26105	VICTORVL	26003	ADELANTO	2	TOLUCA 230/500kV [illegible] "G"	90%	90%	91%	91%
2.	26003	ADELANTO	26079	TOLUCA	1	VICTORVL - VIC16-18 500/287kV [illegible] "K"	95%	97%	98%	101%
	26044	MARKETPL	26003	ADELANTO	1	VALLEY - RINALDI 230kV Line 1	102%	105%	109%	116%
						VALLEY - RINALDI 230kV Line 2	102%	105%	109%	116%

Table 12: Thermal overloads Aggravation at Different EV Charging Levels During On-Peak Conditions

		B0-HSBase			B1-3%G2V			B2-5%G2V			B3-10%G2V		
BUS-NO	NAME	KV	V-PU	KV	V-PU	kV	Delta (kV)	V-PU	kV	Delta (kV)	V-PU	kV	Delta (kV)
26013	AIRWAY	230	1.0000	230.0	0.9978	229.5	-0.5	0.9956	229.0	-1.0	0.9907	227.9	-2.1
26025	HAYNES	230	1.0213	234.9	1.0066	231.5	-3.4	1.0041	230.9	-4.0	0.9985	229.7	-5.2
26286	HAY N	230	1.0144	233.3	1.0119	232.7	-0.6	1.0095	232.2	-1.1	1.0041	230.9	-2.4
26052	OLIVE	230	1.0115	232.6	1.0000	230.0	-2.6	1.0000	230.0	-2.6	1.0000	230.0	-2.6
26061	RINALDI	230	1.0005	230.1	1.0000	230.0	-0.1	1.0000	230.0	-0.1	1.0000	230.0	-0.1
26063	RIVER	230	1.0264	236.1	1.0201	234.6	-1.4	1.0190	234.4	-1.7	1.0165	233.8	-2.3
26066	SCATERGD	230	1.0001	230.0	1.0124	232.9	2.8	1.0103	232.4	2.3	1.0056	231.3	1.3
26068	STJOHN	230	1.0037	230.9	1.0100	232.3	1.4	1.0083	231.9	1.1	1.0046	231.1	0.2
26072	CNTURYLD	230	1.0044	231.0	0.9983	229.6	-1.4	0.9961	229.1	-1.9	0.9911	228.0	-3.1
26078	TOLUCA	230	1.0003	230.1	1.0244	235.6	5.5	1.0223	235.1	5.1	1.0181	234.2	4.1
26268	TOL E	230	0.9988	229.7	1.0095	232.2	2.5	1.0077	231.8	2.0	1.0039	230.9	1.2
26080	VELASCO	230	0.9954	228.9	0.9979	229.5	0.6	0.9957	229.0	0.1	0.9907	227.9	-1.1
26081	ATWATER	230	1.0140	233.2	1.0016	230.4	-2.9	0.9991	229.8	-3.4	0.9935	228.5	-4.7
26086	NRTHRDGE	230	1.0103	232.4	0.9979	229.5	-2.9	0.9955	229.0	-3.4	0.9900	227.7	-4.7
26087	OLYMPC	230	1.0218	235.0	1.0026	230.6	-4.4	1.0000	230.0	-5.0	0.9943	228.7	-6.3
26093	TARZANA	230	1.0109	232.5	1.0125	232.9	0.4	1.0102	232.3	-0.2	1.0051	231.2	-1.3
26094	SYLMARLA	230	1.0133	233.1	1.0118	232.7	-0.3	1.0092	232.1	-0.9	1.0038	230.9	-2.2
26103	VALLEY	230	0.9955	229.0	0.9930	228.4	-0.6	0.9906	227.8	-1.1	0.9849	226.5	-2.4
26014	GRAMERC1	138	1.0085	139.2	0.9923	136.9	-2.2	0.9900	136.6	-2.6	0.9847	135.9	-3.3
26016	HALLDALE-W	138	1.0133	139.8	0.9981	137.7	-2.1	0.9959	137.4	-2.4	0.9907	136.7	-3.1
26260	HALLDALE-C	138	1.0000	138.0	0.9965	137.5	-0.5	0.9943	137.2	-0.8	0.9892	136.5	-1.5
26261	HALLDALE-E	138	1.0000	138.0	0.9927	137.0	-1.0	0.9903	136.7	-1.3	0.9846	135.9	-2.1
26065	SCATERGD	138	1.0113	139.6	1.0113	139.6	0.0	1.0088	139.2	-0.3	1.0033	138.5	-1.1
26069	CNTURY	138	1.0001	138.0	0.9931	137.0	-1.0	0.9905	136.7	-1.3	0.9845	135.9	-2.2
26073	WLMNTN	138	1.0135	139.9	1.0054	138.7	-1.1	1.0030	138.4	-1.4	0.9978	137.7	-2.2
26075	WLMNTNLD	138	1.0144	140.0	1.0084	139.2	-0.8	1.0062	138.9	-1.1	1.0013	138.2	-1.8
26076	FAIRFAX	138	0.9956	137.4	1.0076	139.0	1.7	1.0051	138.7	1.3	0.9996	137.9	0.6
26077	TOLUCA	138	0.9947	137.3	1.0194	140.7	3.4	1.0171	140.4	3.1	1.0122	139.7	2.4
26083	HOLYWD1	138	0.9959	137.4	1.0132	139.8	2.4	1.0110	139.5	2.1	1.0059	138.8	1.4
26084	HOLYWD2	138	1.0078	139.1	1.0132	139.8	0.7	1.0110	139.5	0.4	1.0059	138.8	-0.3
26085	HOLYWDLD	138	1.0107	139.5	1.0052	138.7	-0.8	1.0027	138.4	-1.1	0.9971	137.6	-1.9
26088	OLYMPCLD	138	1.0141	139.9	1.0027	138.4	-1.6	1.0003	138.0	-1.9	0.9949	137.3	-2.6
26089	AIRPORT	138	1.0141	139.9	1.0092	139.3	-0.7	1.0075	139.0	-0.9	1.0037	138.5	-1.4
26091	HARBOR	138	1.0079	139.1	1.0119	139.6	0.6	1.0095	139.3	0.2	1.0041	138.6	-0.5
26092	TARZANA	138	1.0052	138.7	1.0119	139.6	0.9	1.0095	139.3	0.6	1.0041	138.6	-0.2
26095	TAP 1	138	1.0133	139.8	0.9982	137.8	-2.1	0.9961	137.5	-2.4	0.9914	136.8	-3.0
26096	TAP 2	138	1.0003	138.0	1.0010	138.1	0.1	0.9990	137.9	-0.2	0.9945	137.2	-0.8
26102	VALLEY	138	1.0030	138.4	0.9929	137.0	-1.4	0.9905	136.7	-1.7	0.9848	135.9	-2.5
	Average						-0.4			-0.7			-1.6

Table 13: Voltage Degradation at Different EV Charging Levels During On-Peak Conditions

CONT.	CIRCUIT	IMPACTED ELEMENT	HEAVY SUMMER			
			B0	B5-3%V2G	B6-5%V2G	B7-10%V2G
(N-1) NERC Categories B2 and B3						
500kV Lines						
2.	26003 ADELANTO 26079 TOLUCA 1	VALLEY - RINALDI 230kV Line 1	102%	99%	101%	98%
		VALLEY - RINALDI 230kV Line 2	102%	99%	101%	98%
		VICTORVL - VIC16-18 500/287 [illegible]"K"	99%	98%	99%	99%
		RINALDI 500/230kV [illegible]H		90%	90%	90%
(N-2) NERC Category C5						
500kV Lines						
1.	26003 ADELANTO 26115 RINALDI2 1 26105 VICTORVL 26062 RINALDI 1	TOLUCA 230/500kV [illegible]"G"	111%	111%	111%	112%
		TOLUCA 230/500kV [illegible]"H"	114%	113%	113%	114%
		VICTORVL - VIC16-18 500/287kV [illegible]"K"	106%	105%	105%	106%
Common Breaker Mode of Failure NERC Category C2						
500kV Lines						
2.	26003 ADELANTO 26079 TOLUCA 1	VICTORVL - VIC16-18 500/287kV [illegible]"K"	95%	94%	94%	95%
	26044 MARKETPL 26003 ADELANTO 1	VALLEY - RINALDI 230kV Line 1	102%	99%	99%	98%
		VALLEY - RINALDI 230kV Line 2	102%	99%	99%	98%

Table 14: Thermal Overloads Improvement at Different EV Charging Levels During On-Peak Conditions

		B0-HSBase			B5-3%V2G			B6-5%V2G			B7-10%V2G		
BUS-NO	NAME	KV	V-PU	KV	V-PU	kV	Delta (kV)	V-PU	kV	Delta (kV)	V-PU	kV	Delta (kV)
26013	AIRWAY	230	1.0000	230.0	1.0017	230.4	0.4	1.0024	230.6	0.6	1.0047	231.1	1.1
26025	HAYNES	230	1.0213	234.9	1.0221	235.1	0.2	1.0231	235.3	0.4	1.0245	235.6	0.7
26286	HAY N	230	1.0144	233.3	1.0158	233.6	0.3	1.0168	233.9	0.6	1.0188	234.3	1.0
26052	OLIVE	230	1.0115	232.6	1.0126	232.9	0.3	1.0134	233.1	0.4	1.0149	233.4	0.8
6061	RINALDI	230	1.0005	230.1	1.0022	230.5	0.4	1.0033	230.8	0.6	1.0059	231.4	1.2
26063	RIVER	230	1.0264	236.1	1.0279	236.4	0.3	1.0290	236.7	0.6	1.0314	237.2	1.2
26066	SCATERGD	230	1.0001	230.0	1.0018	230.4	0.4	1.0028	230.6	0.6	1.0053	231.2	1.2
26068	STJOHN	230	1.0037	230.9	1.0054	231.2	0.4	1.0062	231.4	0.6	1.0084	231.9	1.1
26072	CNTURYLD	230	1.0044	231.0	1.0059	231.4	0.3	1.0067	231.5	0.5	1.0088	232.0	1.0
26078	TOLUCA	230	1.0003	230.1	1.0021	230.5	0.4	1.0031	230.7	0.6	1.0057	231.3	1.2
26268	TOL E	230	0.9988	229.7	1.0006	230.1	0.4	1.0013	230.3	0.6	1.0038	230.9	1.1
26080	VELASCO	230	0.9954	228.9	0.9974	229.4	0.5	0.9985	229.7	0.7	1.0015	230.3	1.4
26081	ATWATER	230	1.0140	233.2	1.0159	233.7	0.4	1.0172	234.0	0.7	1.0204	234.7	1.5
26086	NRTHRDGE	230	1.0103	232.4	1.0123	232.8	0.5	1.0136	233.1	0.8	1.0166	233.8	1.4
26087	OLYMPC	230	1.0218	235.0	1.0235	235.4	0.4	1.0247	235.7	0.7	1.0276	236.3	1.3
26093	TARZANA	230	1.0109	232.5	1.0120	232.8	0.3	1.0127	232.9	0.4	1.0145	233.3	0.8
26094	SYLMARLA	230	1.0133	233.1	1.0144	233.3	0.3	1.0151	233.5	0.4	1.0167	233.8	0.8
26103	VALLEY	230	0.9955	229.0	0.9976	229.4	0.5	0.9987	229.7	0.7	1.0017	230.4	1.4
26014	GRAMERC1	138	1.0085	139.2	1.0101	139.4	0.2	1.0110	139.5	0.3	1.0132	139.8	0.6
26016	HALLDALE-W	138	1.0133	139.8	1.0145	140.0	0.2	1.0152	140.1	0.3	1.0168	140.3	0.5
26260	HALLDALE-C	138	1.0000	138.0	1.0000	138.0	0.0	1.0000	138.0	0.0	1.0000	138.0	0.0
26261	HALLDALE-E	138	1.0000	138.0	1.0000	138.0	0.0	1.0000	138.0	0.0	1.0000	138.0	0.0
26065	SCATERGD	138	1.0113	139.6	1.0127	139.8	0.2	1.0136	139.9	0.3	1.0159	140.2	0.6
26069	CNTURY	138	1.0001	138.0	1.0019	138.3	0.2	1.0030	138.4	0.4	1.0056	138.8	0.8
26073	WLMNTN	138	1.0135	139.9	1.0143	140.0	0.1	1.0148	140.0	0.2	1.0160	140.2	0.3
26075	WLMNTNLD	138	1.0144	140.0	1.0163	140.2	0.3	1.0176	140.4	0.4	1.0208	140.9	0.9
26076	FAIRFAX	138	0.9956	137.4	0.9977	137.7	0.3	0.9987	137.8	0.4	1.0017	138.2	0.8
26077	TOLUCA	138	0.9947	137.3	0.9966	137.5	0.3	0.9976	137.7	0.4	1.0003	138.0	0.8
26083	HOLYWD1	138	0.9959	137.4	0.9981	137.7	0.3	0.9994	137.9	0.5	1.0026	138.4	0.9
26084	HOLYWD2	138	1.0078	139.1	1.0094	139.3	0.2	1.0106	139.5	0.4	1.0130	139.8	0.7
26085	HOLYWDLD	138	1.0107	139.5	1.0125	139.7	0.2	1.0136	139.9	0.4	1.0163	140.2	0.8
26088	OLYMPCLD	138	1.0141	139.9	1.0149	140.1	0.1	1.0154	140.1	0.2	1.0165	140.3	0.3
26089	AIRPORT	138	1.0141	139.9	1.0149	140.1	0.1	1.0154	140.1	0.2	1.0165	140.3	0.3
26091	HARBOR	138	1.0079	139.1	1.0099	139.4	0.3	1.0111	139.5	0.4	1.0140	139.9	0.8
26092	TARZANA	138	1.0052	138.7	1.0070	139.0	0.2	1.0083	139.1	0.4	1.0110	139.5	0.8
26095	TAP 1	138	1.0133	139.8	1.0144	140.0	0.2	1.0151	140.1	0.2	1.0167	140.3	0.5
26096	TAP 2	138	1.0003	138.0	1.0019	138.3	0.2	1.0028	138.4	0.3	1.0053	138.7	0.7
26102	VALLEY	138	1.0030	138.4	1.0045	138.6	0.2	1.0053	138.7	0.3	1.0076	139.0	0.6
	Average						0.3			0.4			0.8

Table 15: Voltage Improvement at Different EV Charging Levels During On-Peak Conditions

List of Reports Published under this Demo

Demo 20 Report –Report date August 23, 2016

Impacts and Benefits

List of Planned Impacts and Benefits for this Demo

None established.

Realized Impacts and Benefits to Date

None established.

Appendix AR DR Use Case 5

Final Technical Report

Los Angeles Department of Water & Power Smart Grid Regional Demonstration Project Demand Response

Use Cases DR CB-5



USC University of Southern California

Prepared by

SGRDP DR FMS Research Team

Carol Fern, Co-Principal Investigator

University of Southern California

June 30, 2016

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4 RESULTS AND SUMMARY 28

1 Introduction

The commitment to renewable energy, deployment of customer distributed generation and energy storage are reshaping and making less predictable the required electrical generation. Electrical loads are increasing while needing to utilize a long-time established distribution infrastructure. There have been advances in metering technology with real-time communications, building automation and the ability to perform analysis on very large data sets. These new paradigms require and enable the opportunity for developing a demand response program to address these challenges. This document outlines the work performed at the University of Southern California to develop, implement and demonstrate an automated Demand Response Program in support of developing said program for LADWP and other utilities.

The SGRDP Demand Response project will demonstrate the use of existing and new technology on a range of building types to be used as the basis for developing a Demand Response (DR) program. An evaluation of a DR program for a commercial application was performed including:

- Development of an automated communication strategy between the utility and the customer for a demand response event for notification, acknowledgement and load curtailment impact
- Understanding building loads through building to grid metering and the potential for load curtailment
- Assessing demand response strategies; which are the most predictable, sustainable and greatest curtailment impact.
- An assessment of the customer cost to deploy demand response within a facility.

2 Demonstration Environment

The demonstration environment is primarily the University of Southern California (USC) campus', with interfaces to the LADWP Demand Response Server for issuance, receipt and acknowledgement of the Utility initiated Demand Response signal.

First is the physical environment of the demonstration which includes 49 buildings, over 3,658,400 sqft represents a variety of building types including lecture halls, administration and dormitories. These buildings have energy consumption patterns similar to those of typical commercial and

residential customers in a small community, and USC operates very much as a small city. Figure 1 illustrates the buildings enrolled in the demonstration for the University Park Campus and Figure 2 for the Health Science Campus.

The most cost-effective DR will be achievable in buildings already equipped with at least some level of building control system to provide an insight into the operations of a building. All of the buildings selected for the demonstration project have individual building electrical metering at 15 minute intervals and direct digital control of the heating, ventilating and air conditioning (HVAC) equipment. This enabled HVAC demand response strategies to be readily implemented with minimal equipment installation and cost.

Figure 1: USC University Park Campus Automated Demand Response Buildings

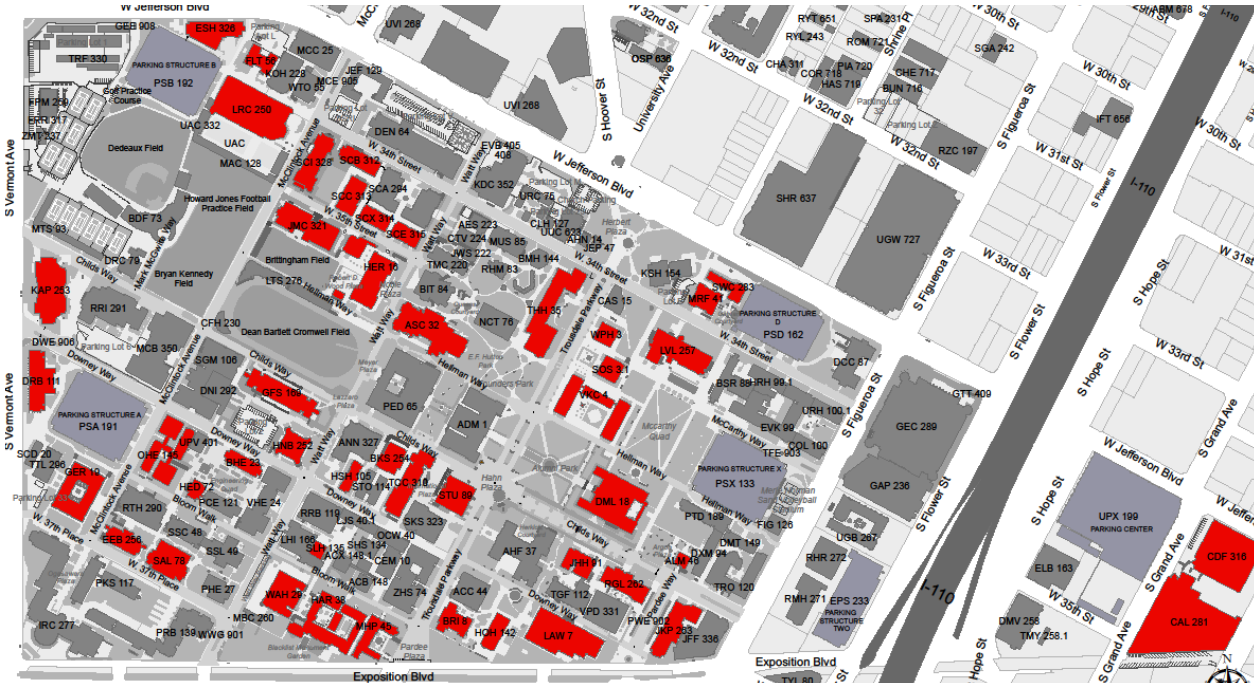


Figure 2: USC Health Sciences Campus Automated Demand Response Buildings



The virtual environment for the demonstration consists of the LADWP Demand Response Automation Server, the Viterbi School of Engineering DDS server, the USC Energy Management System, the USC Electric Metering system (separate from LADWP), the USC Demand Response Communication Server and a language converter server (located off campus).

3 *Large Commercial Customer Participates in DR Program (DR-CB 5)*

The Demand Response Program Use Case CB 5 is a demonstration of Building to Grid (B2G) concepts within the USC campus demonstration environment. B2G describes the interaction of the electrical grid with buildings (commercial) and aligns the end-uses of the building (heating, cooling, lighting, process loads, etc.) to the energy source (electricity, natural gas) serving the end-use. Activities associated with B2G include participation in demand response, as well as diagnostic and energy efficiency analysis within the building itself.

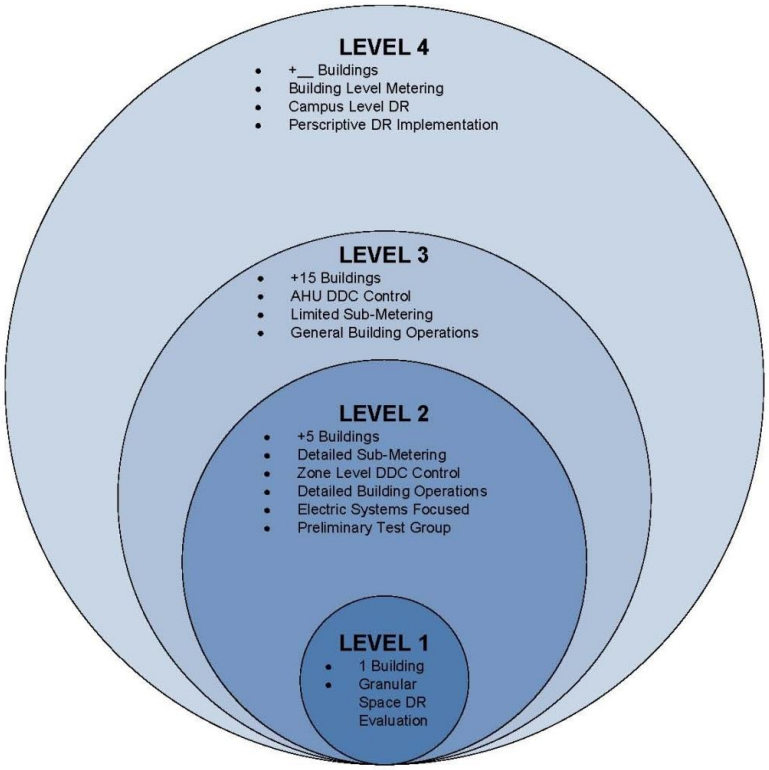
3.1 Key Objectives of the Building to Grid Demonstration

- Provide load profiles (kW) for the building end-use electric components through sub-metering of in a select number of buildings
- Illustrate the interactions between building sub-spaces and/or infrastructure sub-systems for a select number of demand management strategies.
- Conduct DR testing to optimize the load reduction and minimize occupant negative impacts for a given DR request.
- Assessment the impact of weather and operational parameters.
- Demonstrate the impact of demand response strategies on power quality at the building level.

3.2 Methodologies

A strategy which leveraged detailed metering at a select number of buildings to understand the potential of demand response and then use this knowledge to extrapolate to a larger set of buildings was employed. Figure 3 illustrates the strategy. Level 1 has very detailed space data for one building with very granular data and space occupancy information. Level 2 buildings have zone level control, are electric energy use focused, have direct digital control at the zone level and as part of this project had sub-metering installed to understand the building end-uses. The Level 2 set of buildings was the preliminary test bed for assessing demand response strategies. The Level 3 buildings would only have sub-metering if needed to understand building loads further, and would not be required to have zone level direct digital control, but must have direct digital control of the main HVAC equipment including air handlers. Level 3 buildings were used to refine any demand response strategies before applying across additional buildings using prescriptive approaches as represented as Level 4.

Figure 3: Demand Response Building Selection Strategy



3.2.1 End-use load profile development

Building to Grid (B2G) integration is used to identify the energy use of building functions (heating, cooling, lighting etc.), within a building and to identify the greatest opportunities for demand response and/or energy efficiency. To accomplish this, sub-metering (Figure 4) was installed in five USC buildings that captures the end-use load profiles of HVAC Fans, HVAC cooling systems, lighting, emergency power and receptacle loading. These buildings represent a residential building, Fluor Tower, gathering area buildings including Leavey Library and Tudor Campus Center and Commercial / Administrative buildings including Ralph and Goldy Lewis Hall and School of Cinematic Arts Building B.

Figure 4: Electrical Sub-metering Summary

Building	Building Code	Chilled Water System	HVAC Fans	Lighting	Receptable	Total
Leavy Library	LVL	X	X	X	(1)	X
Ralph and Goldy Lewis Building	RGL	(4)	X	X	X	X
Tutor Campus Center	TCC	X	X	(1)	(1)	X
Cinema Building B	SCB	(4)	X	X	X	X
Fluor Tower	FLT	(3)	(3)	X	(2)	X

(1)	Indirectly measured, used total less other end use loads
(2)	Individual kitchen and space loads are measured
(3)	Combined cooling and HVAC fans since packaged units
(4)	Building is on campus wide chilled water loop

Appendix A, contains two examples of metering diagrams or data used to establish the metering that was performed. For end-use metering as for LVL, RGL, TCC and SCB, the electrical single line diagrams are reviewed and meters are placed to capture the specific end-uses. For suite and end-use level metering as is the case for Fluor Tower, individual electrical panel information was mined and each circuit was metered.

3.2.2 Demand Response Strategies

The primary demand response strategies employed for the demonstration project are focused on modifications to the HVAC systems, for the following reasons:

1. A significant portion of the energy used in a commercial buildings is associated with the heating and cooling of the spaces, and specifically for cooling, increases during typically “high peak demand” time periods.
2. Most commercial buildings have some level of building HVAC control in place. This can range from basic start/stop of the equipment to very elaborate control sequences of operation based on a range of factors.
3. Functions such as power to receptacle loads (computers) are typically completely under control of the occupant in order to perform a job and are not centrally controlled making automated control virtually impossible.

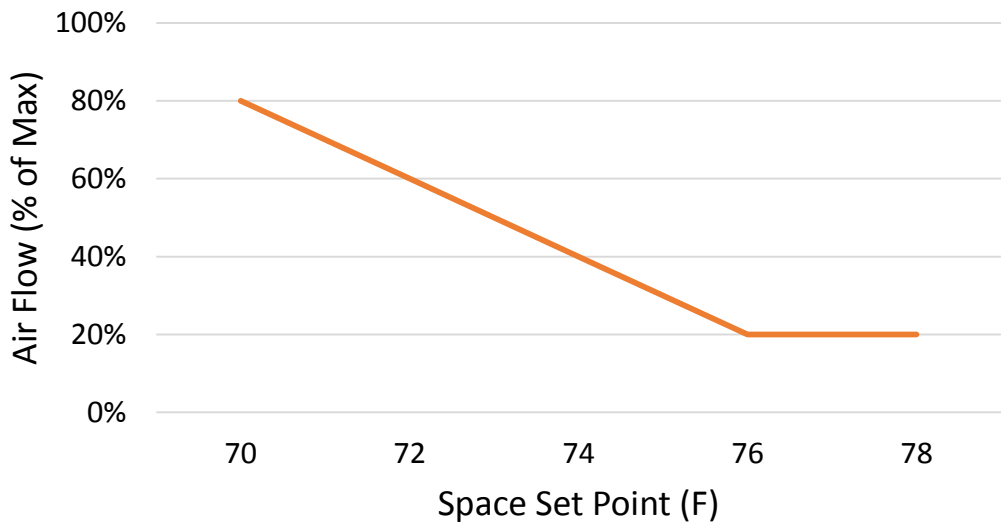
4. Lighting is often not centrally controlled. Demand response strategies can be achieved if dimming control for lighting is available. No lighting DR was explored as part of this demonstration project.

Three strategies were implemented, namely Global Temperature Reset, Variable Speed Drive Reset and Duty Cycling and are explained below.

Global Temperature Reset

Global temperature reset is an indirect demand response strategy, in that changes are made to the building space temperature which intern indirectly impacts energy usage by building systems. The temperature set point of the space is increased; the thermostat compares the space temperature to the reset temperature, and if it is higher, sends a signal to HVAC system. If the HVAC system is a variable air volume system, the VAV box will reduce the amount of air flow to the space (see Figure 5). The reduced air flow requirements by the spaces is "seen" by the fan system, which will indicate to the fan that it can slow down, thereby reducing the fan motor energy. If the HVAC system is a constant volume system, the cooling coil valve will close slightly, reducing the amount of chilled water required from the chilled water system.

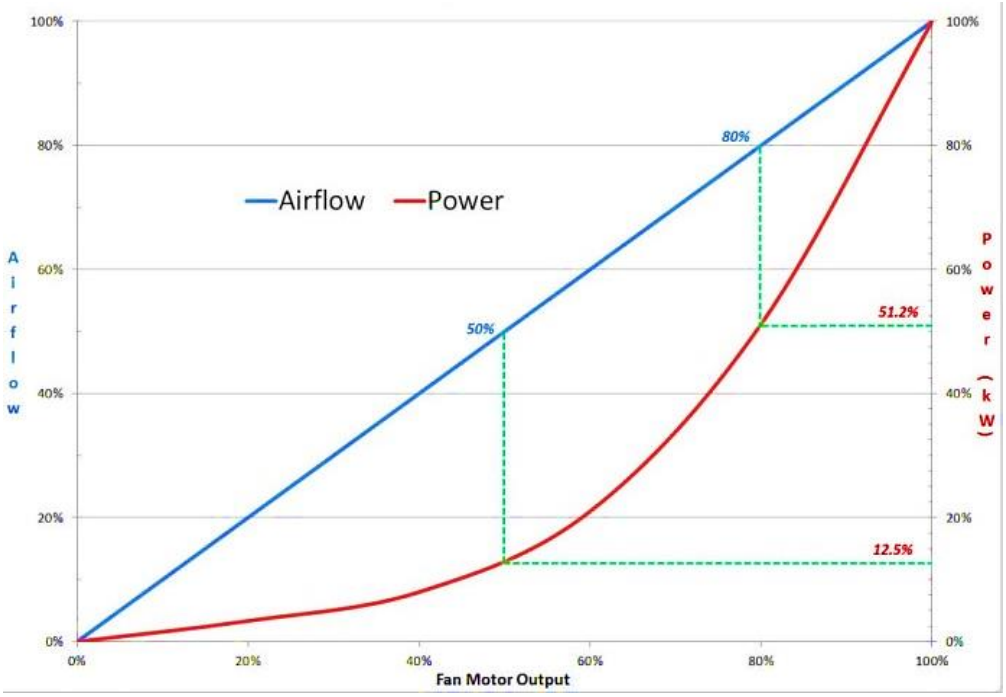
Figure 5: Air Flow to the Space for varying Space Set Point Temperatures at a Fixed Cooling Load



Variable Speed Drive Reset

Variable speed drive reset is a direct demand response strategy, in that changes are made to the energy consuming device directly. The speed of the fan is slowed down, resulting in a reduction in motor energy. The prediction of how much demand response can be achieved is a straightforward calculation once the system profile is mapped. Figure 6 provides a typical electrical versus air flow profile. Note that a drop from 100% to 80% air flow results in an almost 50% drop in power consumption. The specific load curtailment will be based on the actual operating air flow when a DR event is initiated down to what is the standard demand response VFD setting of 50%. Based on the graph example below going from a 100% airflow to 50% air flow results in approximately a 87% reduction in power.

Figure 6: Air Flow versus Fan Output and Power for a Variable Speed Drive

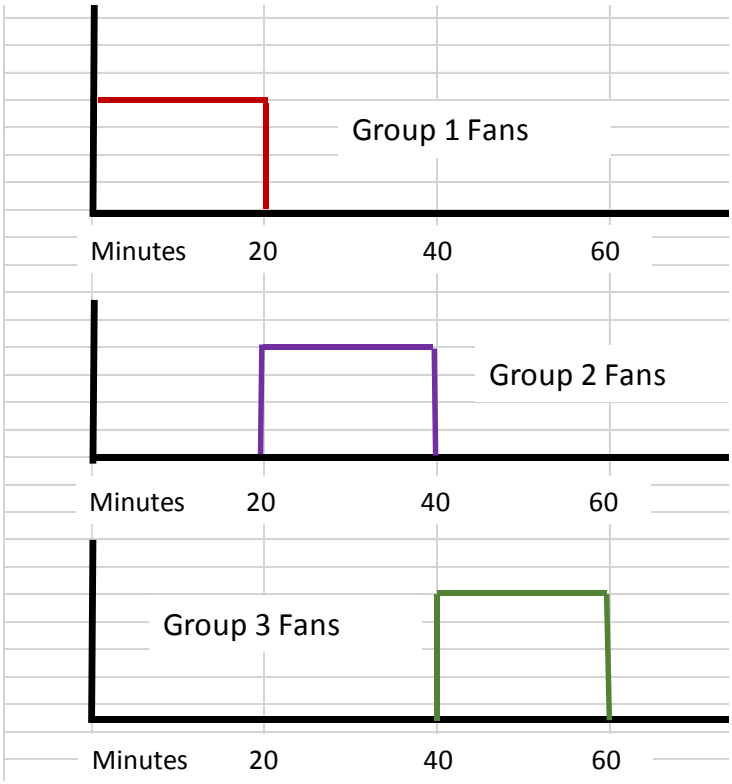


With a reduction in air flow to the spaces, we anticipate that the temperatures in the space will increase over time since the amount of cool air to the space is reduced. If the control system is set up to modify the temperature of the air into the space based on a building parameter (often return air temperature), then the cooling energy may increase, increasing the chilled water system energy usage, but will be more than off-set by the fan energy savings.

Equipment Duty Cycling

Equipment duty cycling is a direct demand response strategy, in that changes are made to the energy consuming device directly. Essentially, the piece of equipment is shut off for a time period. The prediction of how much demand response can be achieved is a straightforward calculation based on a one time measurement of the power usage of the equipment. Duty cycling of fans is performed when a variable speed drive is not available on an air handling unit. Typically, these are smaller fans which serve a suite or small area of a building. Figure 7 illustrates the operation of groups of HVAC equipment to duty cycle during a DR event.

Figure 7: Duty Cycling Diagram with Three Fan Groups



The application of each strategy or combinations of those strategies are analyzed for any given building based on the systems within the building. Figure 8 provides a listing of the buildings and the demand response strategies that were programmed on the USC campus.

Appendix B contains detailed information on the programming logic used to invoke the different DR strategies, while Appendix C contains commissioning and testing forms.

Figure 8: USC Building List and Demand Response Strategies

Building ID	Level 1 GTR	Level 2 VFD	Level 3 Duty	Level 4*	Level 5*	Level 6*
ALM	X	X		X		
ASC		X				
BHE		X				
BKS		X				
BRI	X		X		X	
CAL	X	X		X		
CDF	X	X		X		
DML		X	X			X
DRB	X	X		X		
EEB		X				
ESH		X				
GEC	X	X		X		
GER		X				
GFS	X	X				
HAR		X	X			
HED			X			
HER	X	X		X		
HNB		X				
HOH						
HSH	X	X		X		
JHH			X			
JKP		X				
JMC		X				
KAM		X				
KAP	X	X		X		

Building ID	Level 1 GTR	Level 2 VFD	Level 3 Duty	Level 4*	Level 5*	Level 6*	Level 7*
LAW		X					
LHI		X					
LRC	X	X	X	X	X	X	X
LVL		X					
MHP	X		X		X		
MRF		X					
OHE	X		X		X		
RGL		X					
SAL		X	X				
SCB	X	X		X			
SCC		X					
SCE		X					
SCI		X					
SCX	X	X		X			
SLH			X				
SOS	X	X		X			
SST	X	X		X			
STU	X	X		X			
SWC	X	X		X			
TCC	X	X		X			
THH		X	X				
VKC		X	X			X	
WAH		X					
WPH	X	X	X	X	X	X	X

Level 4: Level 1 + 2
Level 5 : Level 1 + 3
Level 6: Level 2 + 3
Level 7: Level 1 + 2 + 3

A separate Building Audit Report has been issued which presents detailed information on the individual buildings operations and the demand response strategies analyzed for each.

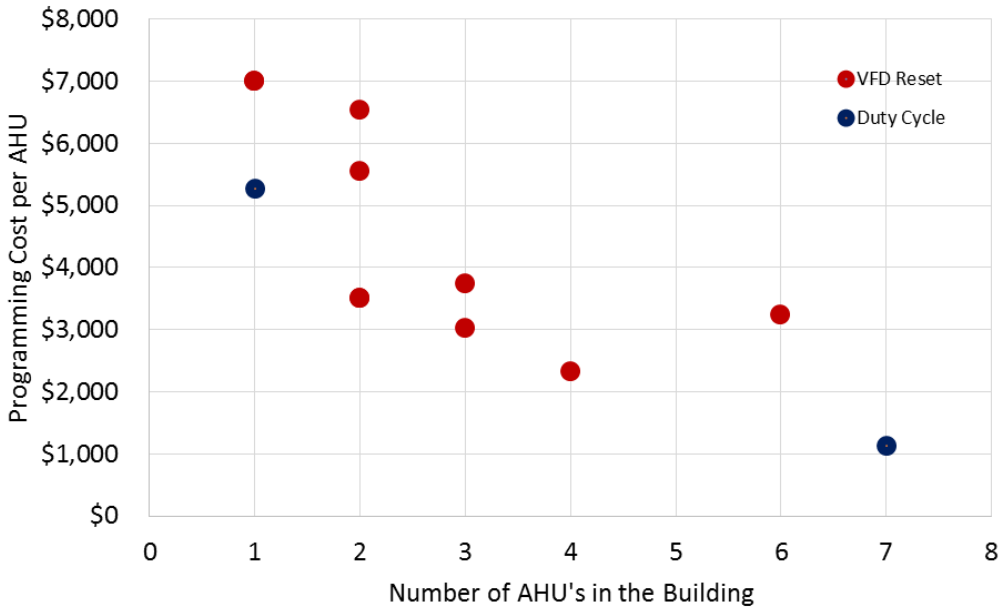
3.2.3 Testing and Optimization

Testing and optimization of the demand response strategies was performed across all buildings, over a range of climate (summer, winter, fall/spring) and operating conditions (weekdays, in-session, out-of-session). This data was used to refine the HVAC programming, ensure continued operation of the DR strategies and provide data for load curtailment prediction. Appendix D provides the calendar testing dates throughout the project.

3.2.4 *Demand Response Strategy Economics*

The University has in-place a significant energy management system based on direct digital controls and an energy control center which consolidates building information which enables remote monitoring and control. Each major piece of equipment can be scheduled on/off and operating parameters can be adjusted to meet the space needs. The cost to invoke demand response strategies, given this infrastructure, are programming and commissioning (essentially no little additional hardware is required). It is with this understanding that the costs for performing the programming for *only* the demand response strategy for a building (excludes automated communication with DWP and VSoE DDS, electrical metering and any additional supporting systems) are presented in Figure 8.

Figure 8: Demand Response Strategy Programming Costs



3.3 Observations and Results

3.3.1 Building to Grid Results

Metering was installed and dashboards developed so that continuous monitoring of electrical usage by end use can be used to understand the load profiles of given equipment and trace the impacts of demand response strategies. End use load profiles were developed to identify the largest energy users within the buildings to quantify demand response opportunities.

Load Curtailment Potential

Figure 9 illustrates the percentage of electrical peak demand by system type for the Leavy Library (LVL) Building. This building has its own chilled water plant, so a large portion of the electricity used at the building is for cooling the spaces. In reviewing the end-uses for demand response, we cannot impact systems which are on the emergency power feed for the building. Receptacle loads are determined by individual building users, making them difficult to manage for demand response. The lighting system is a relatively small portion of the load, and for this building, is not controlled from a single system, again making it more difficult to manage for demand response. The HVAC (fan system) and chiller system which account for approximately 60% of a peak demand are controlled centrally and provide the largest opportunity for demand response.

Figure 9: Electrical End-Use Disaggregation for Leavy Library (LVL)

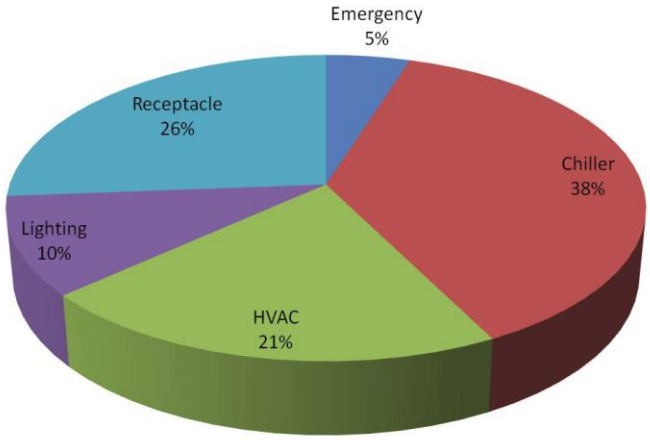
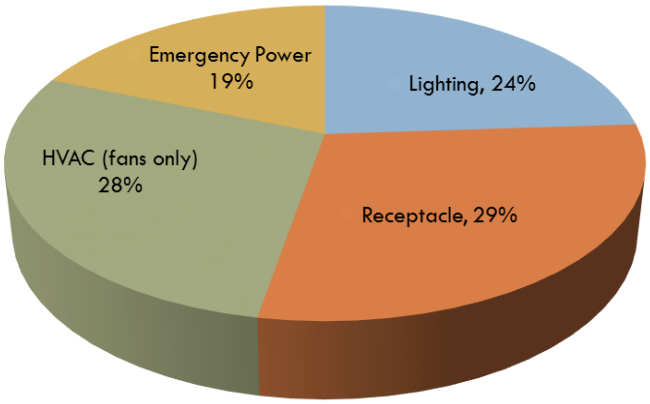


Figure 10 illustrates the percentage of electrical peak demand by system type for the Ralph and Goldy Lewis (RGL) Building. This building is on the campus wide chilled water loop, therefore there is no energy usage associated with chiller operation at the building level.

Similarly, as for the Leavy Library building, control of the emergency power system is not permitted and the receptacle loads are difficult to manage for demand response. Lighting within the building is based on occupancy sensors, so will automatically shut off during the day. The lighting system does not have dimmable control, so only on-off control is available, limiting the opportunity for demand response control. The target for demand response will be the HVAC (fan) system.

Figure 10: Electrical End-Use Disaggregation for Ralph and Goldy Lewis Building (RGL)

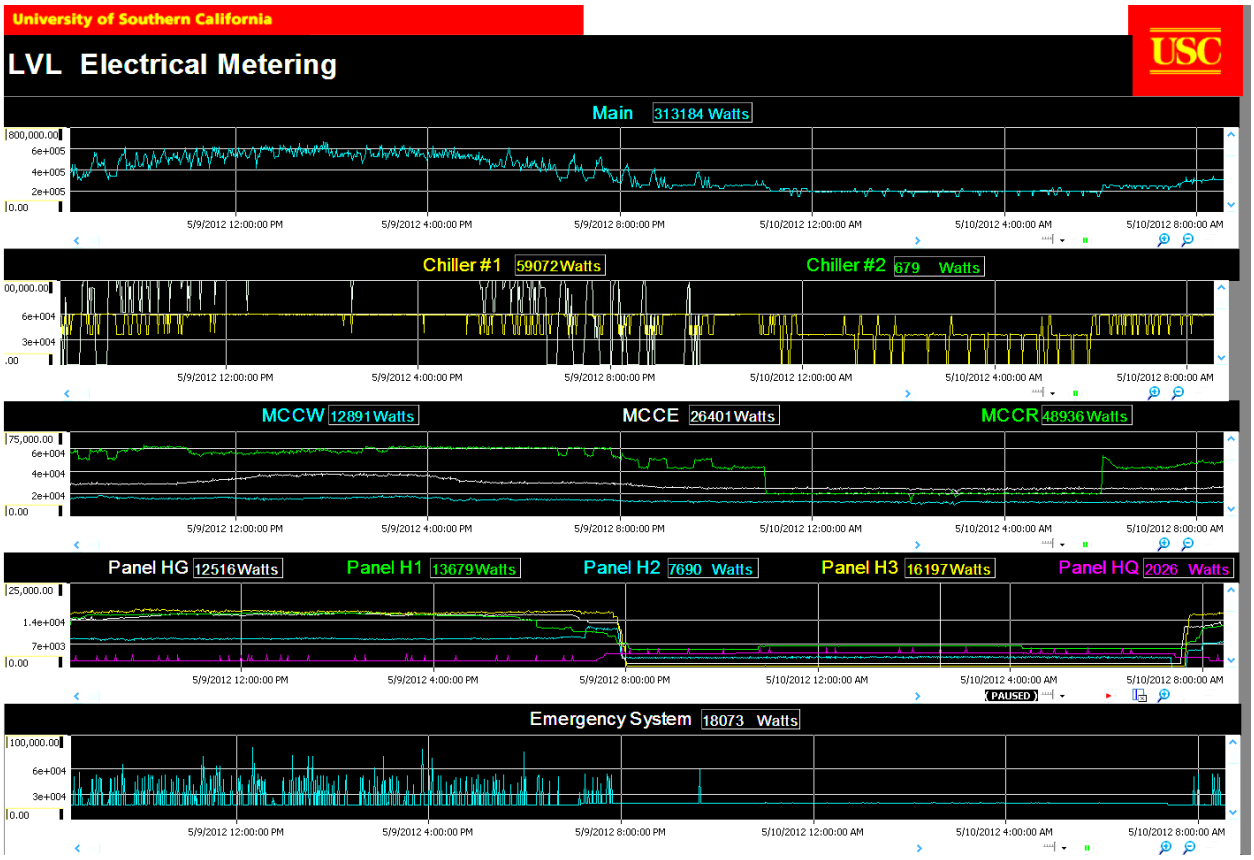


In general, HVAC electrical usage is 30-50% of the electrical load. Of this load, 30-50% can be curtailed during a demand response event.

End-Use Electrical Load Profile Dashboards

The end-use metered data was brought into the USC Energy control center (ECC) front end to provide real time monitoring and display of the information. The amount of energy used by each building system varies over time based on the needs of the building. Figure 11 is a screen capture of the electrical data for Leavy Library building.

Figure 11: Screen Capture of Electrical End-Use Profiles for Leavy Library Building



To understand the impact of building functions on building electrical usage, tests of operation were performed as well graphic display pages were developed which show the operating characteristics of the systems. For example, an air conditioning system includes a fan which blows hot or cold air throughout the building. Most medium to large commercial buildings have a variable air volume system, which varies the amount of air into the building based on the load. The greater the need for cooling or heating the more air that is circulated in the building to keep the space cooled or heated. A signal is sent to the fan to speed up or slow down based on the heating (or cooling) load. So, by changing the fan speed, we change the power draw of the motor and hence energy use for this building function. Figure 12 is a screen capture which illustrates fan speed, fan motor amps and the resulting end use metering for HVAC.

Figure 12: Screen Capture of Fan Speed and Amps and HVAC Electric Use



Equipment Operations and Energy Efficiency Opportunities

Detailed metering is also used to drill down into the electrical profile of the equipment and its operation to identify any operating issues and areas for improvement. Figure 13, illustrates the electrical usage for the chiller within the Leavy Library. This cycling pattern indicates that the chiller is turning on and off on a very short cycle which leads to excessive wear on the unit and inefficient operation. This information was used to reprogram how the chiller responds to cooling needs within the building. Additionally, we were able to determine the efficiency of the chiller plant and a more efficient chiller system was installed. Figure 14 illustrates chiller operation after the re-programming and with the new chiller installed which has significantly reduced the peak electrical demand and the cycling of the equipment.

Figure 13: Chiller Electric Usage Profile illustrating Chiller Compressor Cycling

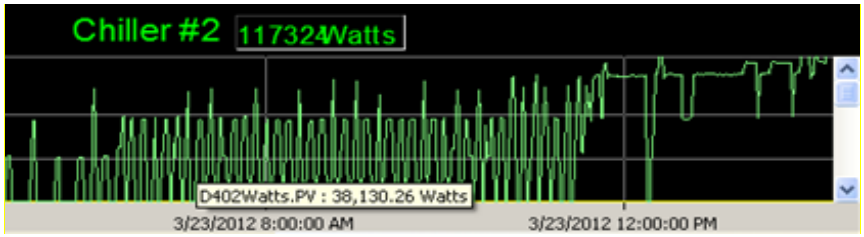
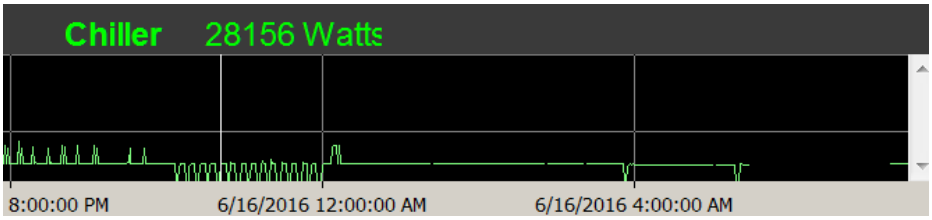


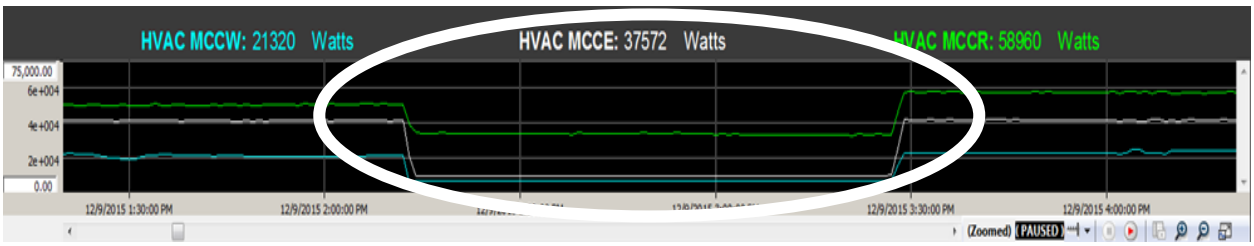
Figure 14: Chiller Electric Usage After Re-programming



Building Sub-system Interactions

To demonstrate the interaction between building sub-systems, the results from a Variable Frequency Drive (VFD) reset demand response strategy at Leavy Library (LVL) building on December 9, 2015 2:15pm to 3:40 pm are illustrated in Figures 15 to 17. A VFD DR strategy reduces the speed of the fan directly reducing the amount of energy used by the fans. Figure 15 illustrates screen capture of the direct load curtailment response of the reduced VFD setting. An abrupt and stable drop in fan energy electrical usage is achieve, of approximately 60kw.

Figure 15: Leavey Library HVAC (Fan) Operation



As a result of the lower VFD setting on the fan the air flow is reduced. With this reduced air flow there is a reduction in the amount of cooling needed. This reduced chilled water load results in a reduction in chiller operation. Figure 16 illustrates the reduction in chilled water electrical usage during the DR event.

Figure 16: Leavey Library Chiller Electrical Load Profile

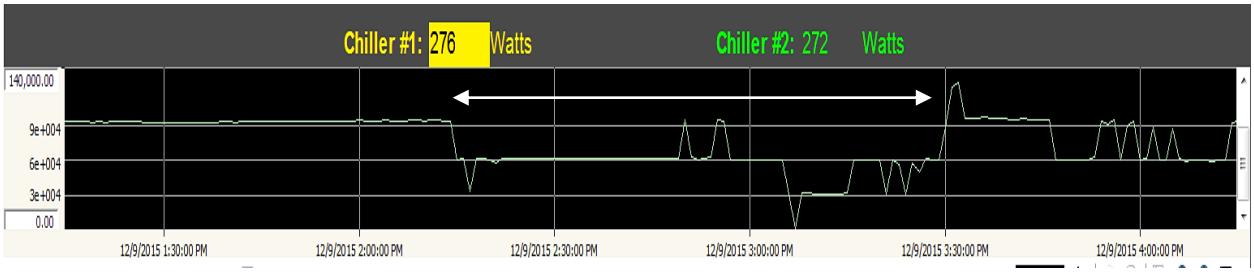
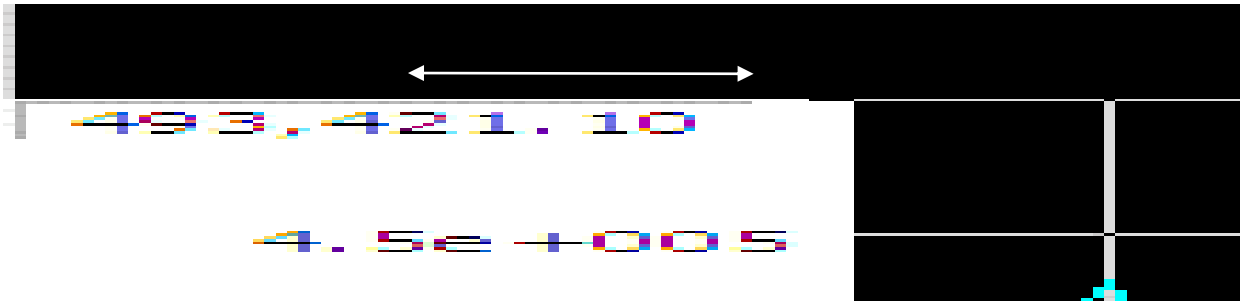


Figure 17 provides the overall building electrical load profile during the DR event. The direct demand response action of VFD reset provided 61kw of curtailment, which intern reduced the chiller requirements provide an additional 97kw reduction, for a total reductin of 158 kw. The secondary building system impacts can be as large or larger than the primary demand response action depending upon the efficeincy of the building system.

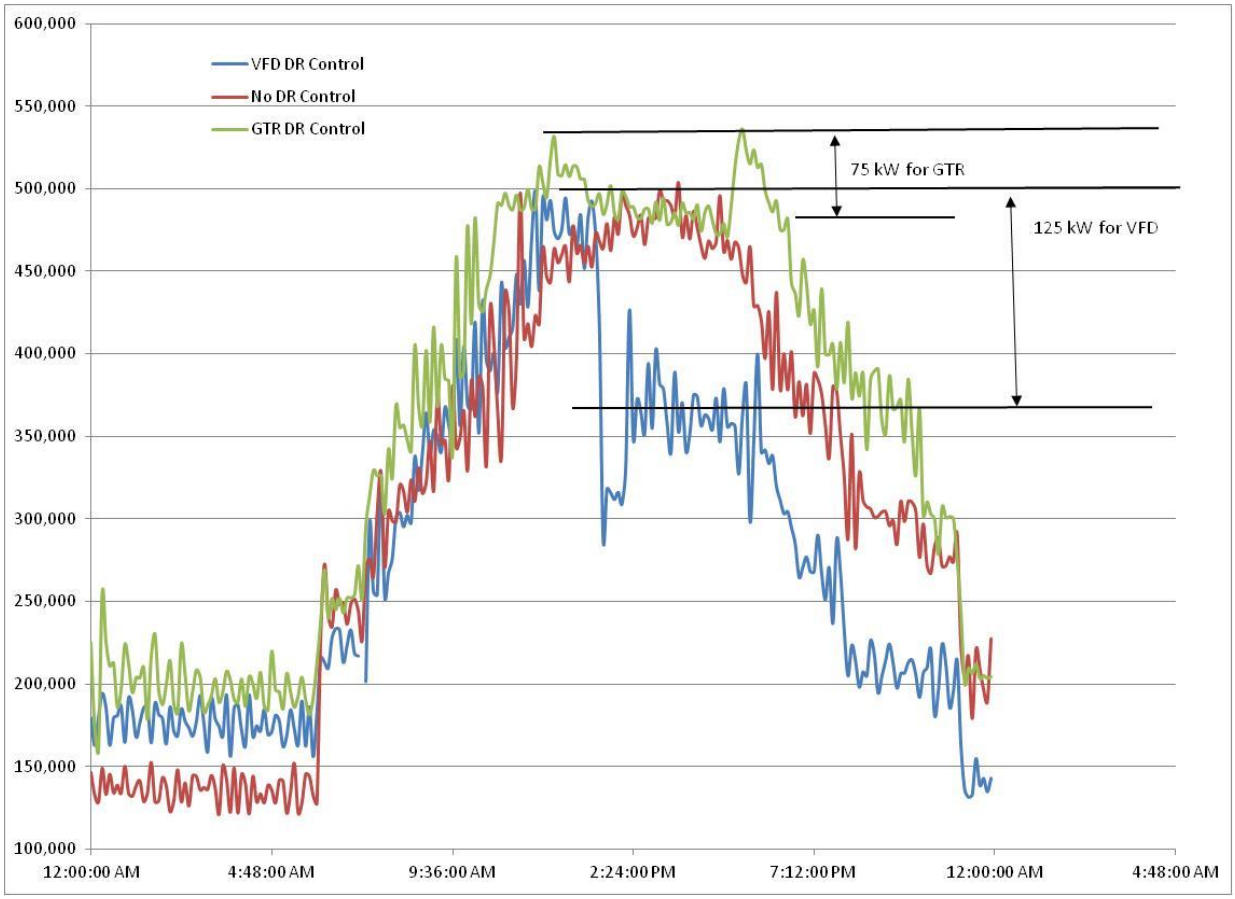
Figure 17: Leavey Library Main Electrical Load Profile



3.3.2 Demand Response Optimization

For each building, the individual demand response strategies were tested. Figure 18 provides an example of demand response comparison between Global Temperature Reset (GTR) and Variable Frequency Drive (VFD) reset for a given building and reviewing the stability of the load curtailment.

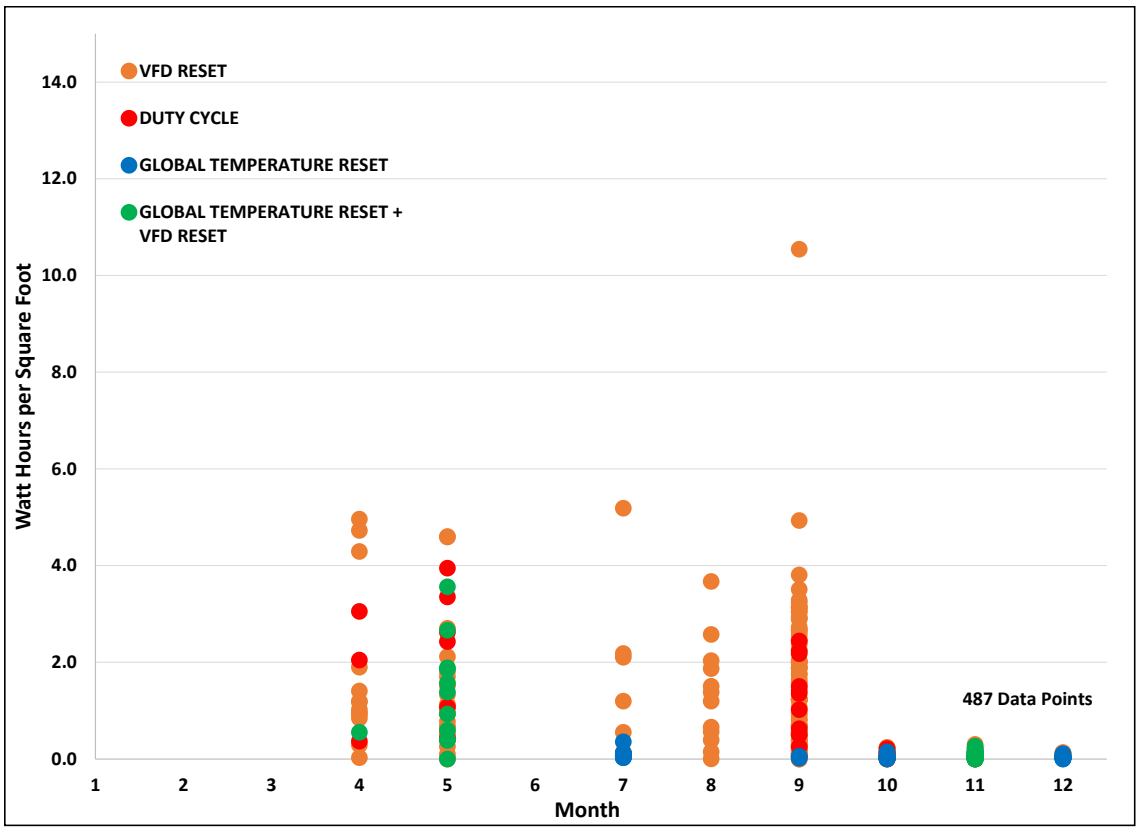
Figure 18: Demand Response Strategies Load Profiles Example



The different demand response strategies for the 49 buildings were tested throughout the year to address impact based on outside conditions and operations. Appendix E contains the results for each building, while Figure 19 illustrates the overall electrical impact by strategy by month. Note, that across the months, the VFD reset strategy (either alone or with Global Temperature Reset) has, on average, provided the greatest W per sqft impact as compared to the other strategies. Note that the impact of demand response during cool months (Oct, Nov., Dec.) are minimal, since the demand on cooling and air flow are already low and a DR impact is

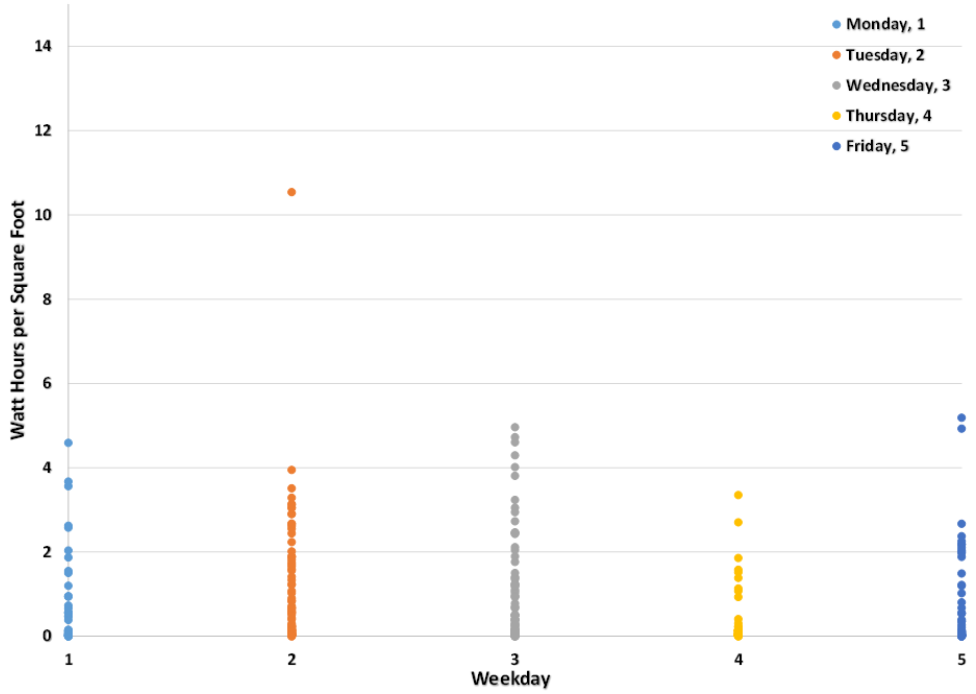
negligible. Demand response impact for June through August are also reduced, since the campus is in summer session, which has a much lower usage and therefore the systems are not operating at full load prior to the demand response event. For buildings and facilities which do not have a "reduced operational season", it is anticipated that similar results as April, May, and September would occur during the cooling season. When school is in full session (April, May and Sept) and in cooling, the demand response impacts average 1.4 w/sqft.

Figure 19: Demand Response Strategies versus Electrical Impact (W/sqft) by Month for All Buildings



The demand response strategies impact as compared to operational data, which for the University is relative to day of the week, is illustrated in Figure 20. There is no significant difference between weekday demand response impacts.

Figure 20: Demand Response Strategies versus Electrical Impact (W/sqft) by Day of the Week



3.3.3 Occupant Impacts

The demand response strategies disrupt the normal operations of providing HVAC to the spaces. The impact of these strategies on occupant comfort is dependent upon overall occupancy levels in the building, the mass of the building to keep the space cool, outside conditions, and location of the occupant in the building relative to the HVAC system. Imbedded into the demand response strategies are continuous monitoring of the space temperatures and not permitting them to rise above acceptable industry standard values. If space temperatures approach the high side of the acceptable temperature, then the degree to which the strategy is used is decreased. For example, if the VFD is operating at 50% and the spaces are reaching the upper limit, the VFD will be sped up to 65% to keep the space temperature reasonable. Also, a minimum amount of air flow to the spaces will be maintained within a time period, by either reducing air flow rates or maintaining that level or through cycling the fan on for a time period every hour.

Occupant comfort is also monitored based on calls received into the USC Customer Resource Center.

Figure 21 shows the Occupant Comfort calls from October 2013 to May 2016 for only Demand Response Buildings and for only the 1 – 5pm potential Demand Event window. The table reports the number of DR events and the total number of buildings involved in all DR events. The number of calls that can be attributed to Demand Response and the number of all Comfort calls (during that DR

window) are listed providing a percentage of number of comfort compliant calls within a month associated with the DR event.

During the entire testing period, 11% of the calls can be attributed to the Demand Response Event. When the testing at USC first started, an aggressive VFD reset speed to 30% was used. We found this setting was too low and in December 2014 a global change to a minimum speed of 50% was established. This resulted in a dramatic reduction in DR related comfort calls showing that 4.2% of the comfort compliant calls are associated with the DR event.

During the earlier testing, we also identified one specific room, in one building which was the basis of many of the comfort related calls. As a result of the customer call, we would take the whole building out of the DR event. We were able to make modifications to the HVAC for the space, eliminating this issue, and enabling the building to remain in future DR events throughout the entire DR window.

Figure 21 Reported via USC Customer Resource Center Occupant Comfort Issues for Demand Response Buildings from 1pm to 5pm.

Month	Number of Events	Total Number of Buildings Tested	Total DR Related Calls	Total Hot Calls 1-6PM All DR Buildings	Percent of DR Calls to Total Calls	
Oct-13	4	144	12	29	41.4%	
Nov-13	7	176	4	23	17.4%	
Dec-13	3	60	4	26	15.4%	
Jan-14	10	23	6	28	21.4%	
Feb-14	10	30	2	32	6.3%	
Mar-14	7	1	0	24	0.0%	
Apr-14	2	36	8	22	36.4%	
May-14	6	106	4	30	13.3%	
Jul-14	1	11	2	36	5.6%	
Aug-14	3	25	3	36	8.3%	
Sep-14	7	139	20	82	24.4%	
Oct-14	6	71	8	40	20.0%	
Nov-14	14	132	10	37	27.0%	
Dec-14	2	41	1	13	7.7%	
Jan-15	1	17	1	28	3.6%	
Feb-15	1	31	1	19	5.3%	
Mar-15	1	39	1	30	3.3%	
Apr-15	1	25	0	28	0.0%	
Jul-15	1	18	0	29	0.0%	
Aug-15	2	37	3	59	5.1%	
Sep-15	1	30	4	26	15.4%	
Oct-15	1	26	3	37	8.1%	
Dec-15	1	10	0	14	0.0%	
Mar-16	1	10	1	21	4.8%	
Apr-16	6	47	3	28	10.7%	
May-16	7	52	2	13	15.4%	

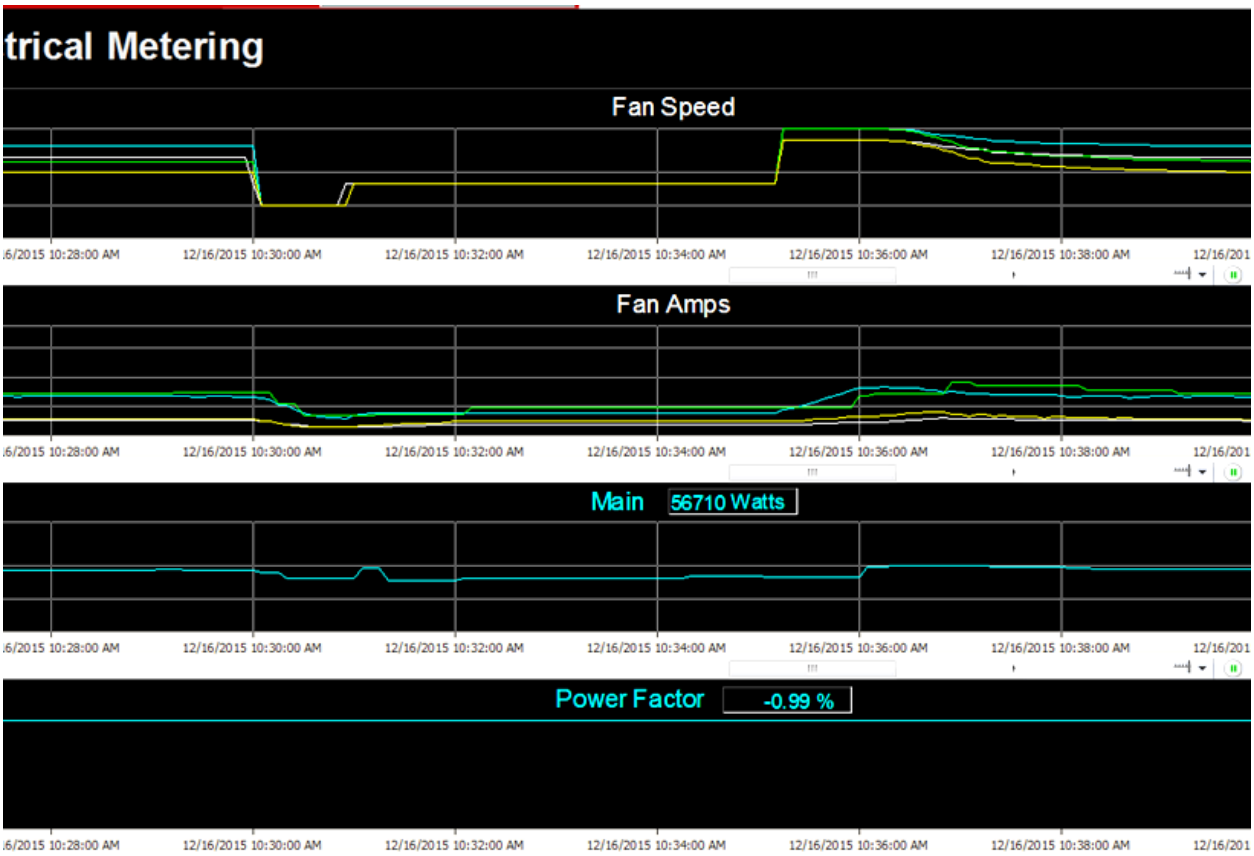
	Number of Events	Total Number of Buildings Tested	Total DR Related Calls	Total Hot Calls 1-6PM All DR Buildings	Average DR calls to Total Calls	Avg After Dec-14 Change
	106	1337	103	948	10.9%	4.2%

3.3.4 Demand Response Power Quality Impacts

The demand response strategies used in this program abruptly change the operation of rotating equipment. Abrupt changes in operation have called into question whether power quality is negatively impacted. To assess this impact we have analyzed data starting at the fan control, through the building, and then from the building to the electrical feeder.

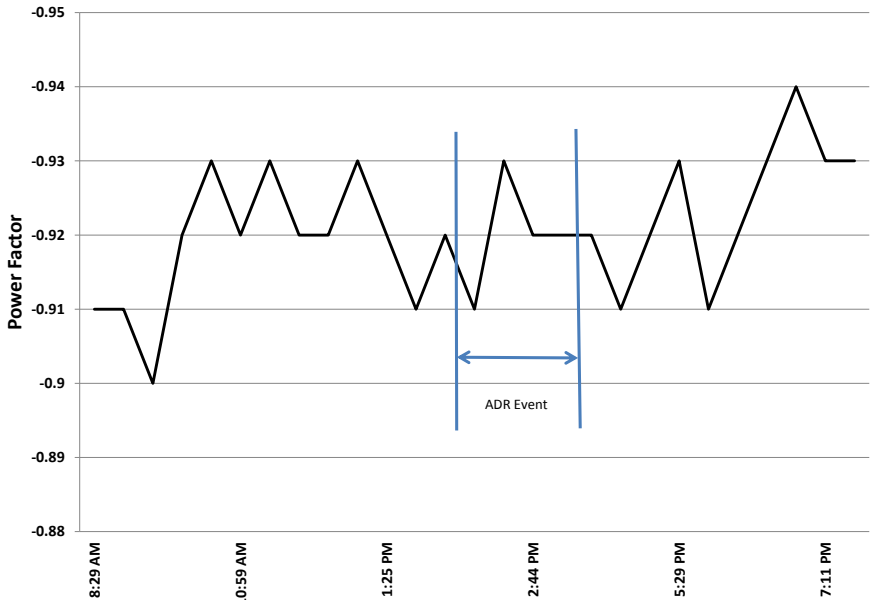
As changes are made to the operation of a building, and specifically an abrupt adjustment to variable speed drives (from 100% to 50%), the impact of these changes to power quality is of interest. Trending of a variable speed drives, for fan speed, fan amps, building main power and the corresponding power factor and total harmonic distortion data was brought into the USC energy control center for monitoring. Figure 22 illustrates that the power factor for the building metering does not change during or after an abrupt change in signal to a variable speed drive.

Figure 22 Screen Capture of Building Electrical Load Profile during VFD Strategy



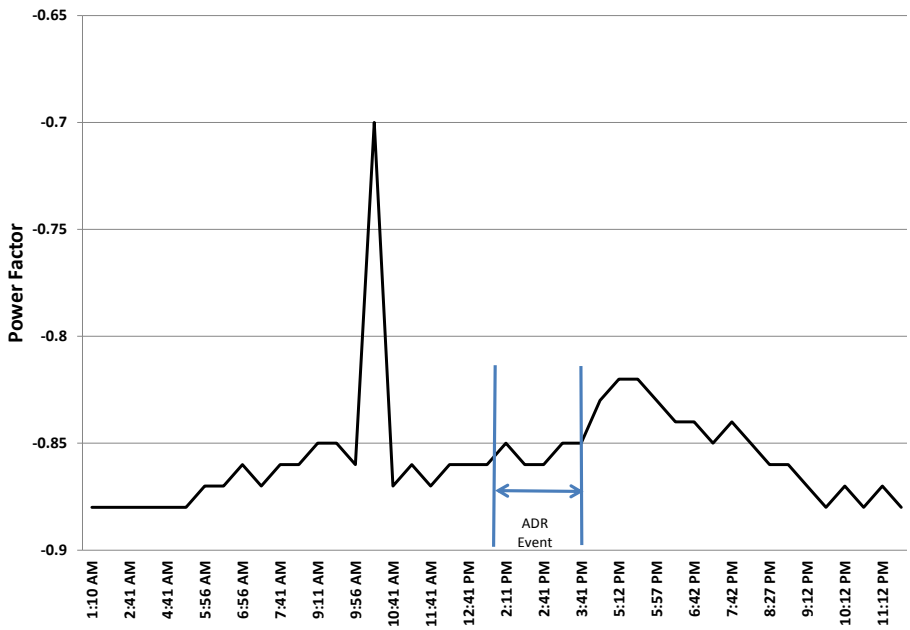
The impact of duty cycling for demand response on the power quality of an electrical building meter is illustrated in Figure 23.

Figure 23 Power Factor Profile for Duty Cycling Building including a DR Event



The impact of demand response in several buildings on the power quality of an electrical feeder was evaluated. Sixty percent (60%) of the buildings on the given electrical feeder (Jefferson vault Feeder Q) were engaged in demand response at the same time. Figure 24 illustrates that the power factor during the DR event did not vary any greater than without the DR event.

Figure 24 Feeder Q Power Factor Profile Including a DR Event



Based on the metering and reporting, there does not appear to be an impact on the power factor at the building or feeder level for the demand response strategies used in this project.

4 Results and Summary

The summary of accomplishments in this demonstration are listed below:

- ✓ Identification of end-uses and quantification of demand response potential for commercial buildings
- ✓ 49 buildings enrolled into the SGADR covering a total of 3,658,400 sqft of various purpose building space.
- ✓ Development of 6 DR strategies, programmed, tested and deployed throughout the campus
- ✓ Developed a building level dashboard for each building in the DR program to monitor, control and report building operations, enabling individual air handling unit opt-in and opt-out capabilities.
- ✓ Developed a summary dashboard to monitor, report, and track the overall demand response event
- ✓ A dashboard to track hourly curtailment and strategies by building.
- ✓ Installed Triduim Jace equipment and programming software to handle the balance of DR system communication and control and a regiment for building equipment operational testing and verification for optimum performance of ADR events occurs regularly
- ✓ Successful automated DR communication from DWP to USC's buildings and estimates and achieved values communicated back to LADWP from the DDS Policy Engine for the entire event and by building.
- ✓ Migrated from FTP communication to Eaton Gen64 Flat Files for faster, nearly instant energy reading transmission.
- ✓ Based on the metering and reporting performed during this program there does not appear to be an impact on the power factor at the building or feeder level for the demand response strategies used in this project.
- ✓ Monthly testing and storyboards were completed for 21 months.
- ✓ Successful Automated DR presentations to Department of Energy on several occasions
- ✓ Submitted required reports

Monthly tests of the automated Demand Response Communication protocol were conducted and screen captures of the events which illustrated the communication between the entities have been provided. Appendix F, illustrates one set of the screen captures. Figure 26 provides a table recording the monthly tests and the results.

Figure 26: Example of Monthly Automated Demand Response Communication Testing

Date	DWP Communication (Confirm/Fail)	USC Communication (Confirm/Fail)	EC/VSoE Communication (Confirm/Fail)	Estimated Curtailment (KWh)	Observed Curtailment (KWh)	Comment
10/30/2014	Confirm	Confirm	Confirm	2040	1097	Nominal test - some buildings not automatically engaging
11/12/2014	Confirm	Fail	Confirm	1488	1571	ADR-JACE not receiving curtailment data
12/30/2014	Confirm	Confirm	Confirm	1412	1415	Final Obs not sent to DWP in time
…						

Figure 27 illustrates the electrical load profile for one Demand Response Event during the demonstration period. Note that USC has a thermal energy storage system which is operated during the on-peak period which results in an approximate 5MW reduction in demand. The load curtailment during this demand response event provided an additional 560 kW (average) during the on-peak window. Figure 28 illustrates the additional cooling energy saved during the DR event as a result of the strategies deployed on the campus.

Figure 27: USC UPC Electrical Load Profile for a Baseline and Demand Response Day

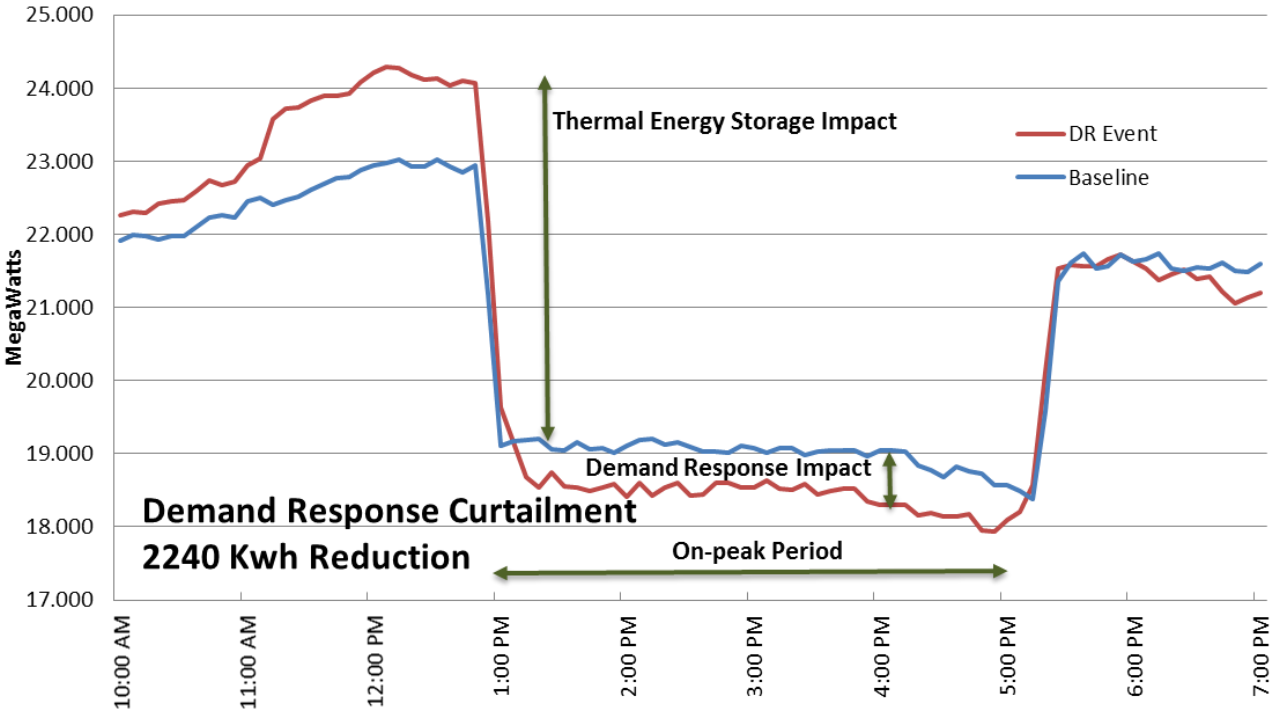
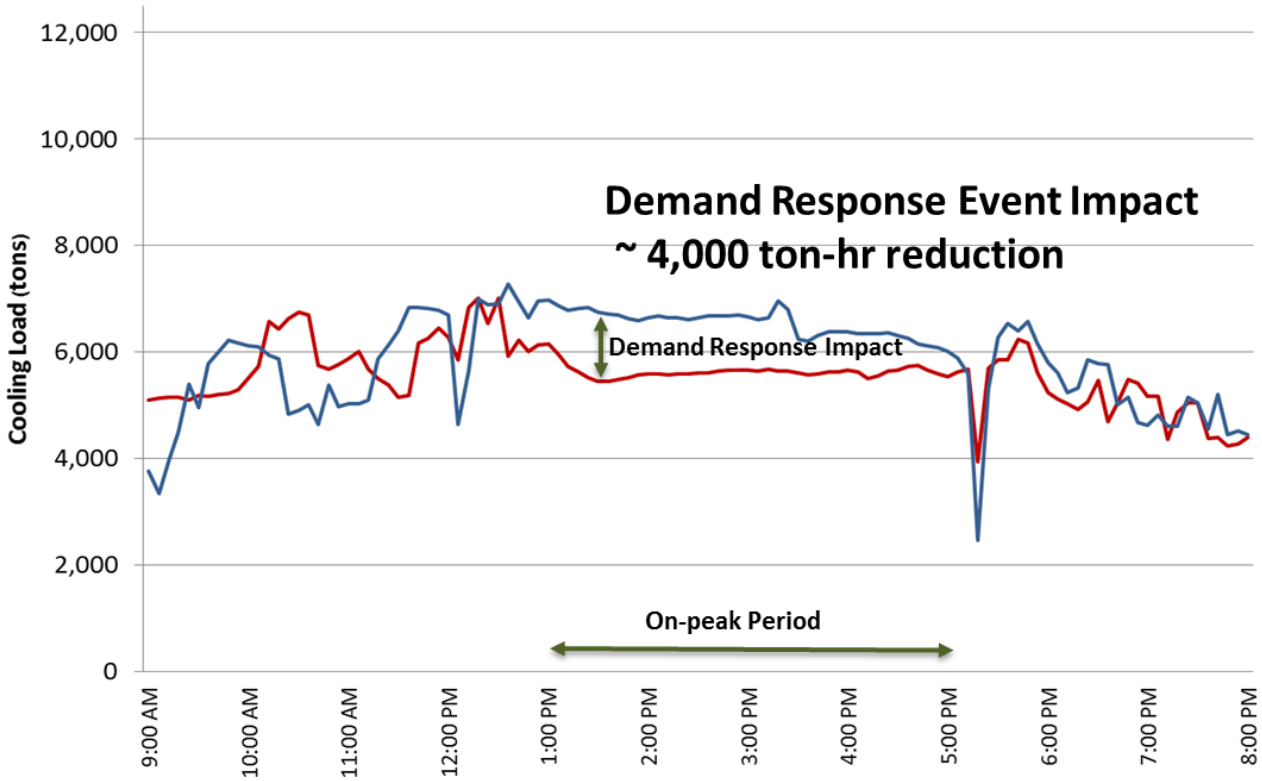


Figure 28 USC UPC Electrical Load Profile for a Baseline and Demand Response Day



Best Practices/ Lessons Learned

When Demand Response was first planned an aggressive reduction of VFD speeds to 30% was implemented. While at times during the normally mild weather this minimal VFD speed was acceptable during all but the hottest days on some buildings. We set a global change to the Stage 1 setting for VFD Reset from 30% to 50% with Stage 2 setting for VFD Reset to from 50% to 65%. For repeat occupant complaints, additional measures were taken such as building air balancing, specific air handler VFD stage setting increase above the established value, and potentially to manually opt out specific systems during events on the hottest days of the year. Though we did find some buildings with better thermal mass and energy efficiency construction were able to handle the minimal air flow without significant occupant complaints, i.e. less than 15% DR event complaints when compared with nominal occupant complaints.

With a system as complex is this, it is important when even performing a small change, it can drastically affect the downstream systems. A full team meeting to discuss the change and follow-up with system-wide testing after any and all changes to ensure all systems work appropriately.

Appendix AS Use Case DR 1-3

DWP Report

Los Angeles Department of Water & Power Smart Grid Regional Demonstration Project

Prediction Models and Analysis

Demand Response

Use Case DR-1-3



Prepared by

Viterbi School of Engineering DR Research Team

Viktor K. Prasanna, Principal Investigator

August 10, 2016

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1. ***Scope and Assumptions***

This study aims to evaluate various forecasting models on their ability to predict power consumption time series. The ARIMA, Static and Data Driven / Dynamic Models considered in this study are used on the same dataset and compared in a principled consistent manner under some assumptions that are made due to the specifics of the dataset and required output. The assumptions made for the models are the following:

- The available power consumption data is divided into 15 minute intervals.
- The prediction temporal horizon is either 1-5pm (16 intervals / values corresponding to heavy consumption hours) or from midnight to midnight (96 intervals / values entire next day).
- We use MAPE (Mean Absolute Percentage Error) to assess the predictive accuracy of our models.
- The dataset's power consumption values are aggregated values over a varying degree of granularity. Namely, our dataset consists of values aggregated over 1,000, 5,000, 10,000 and 50,000 measurements.

2. *ARIMA*

We begin by providing a brief description on ARIMA.

2.1 *Dynamical model for time series*

The Dynamical time series consumption model uses the **Autoregressive Integrated Moving Average (ARIMA) Statistical Model** for making predictions. It is a dynamic model, so it has to be trained before being used for predictions. It uses only historical interval data for training, so the only features present in the training data are the timestamp and KWh usage value for a customer for a certain (historical) time period. The trained model can then be used for making predictions.

ARIMA is a time series prediction model, used for forecasting. An ARIMA model is defined in terms of three non-negative parameters: p, d, and q.

p: the autoregressive order, that denotes the number of past observations included in the model

d: the number of times a time series needs to be differenced to make it stationary

q: the moving average order that denotes the number of past white noise error terms included in the model

These parameters are determined using the autocorrelation and partial autocorrelation functions, using the Box-Jenkins test. Given a time series of real numbers X_t, the ARIMA model is defined as:

$$\left(1 - \sum_{i=1}^{p'} a_i L^i\right) X_t = \left(1 + \sum_{i=1}^{\mathrm{q}} \theta_i L^i\right)\varepsilon_t,$$

where L is the lag operator, α_i are the parameters of the autoregressive part of the model, θ_i are the parameters of the moving average part and ε_t are error terms. The lag operator is defined as $\mathrm{L^i y_t} = \mathrm{y_{t-i}}$.

Advantages of ARIMA include the fact that it does not require domain knowledge, nor does it depend on other features. However, even if computational methods have been proposed to automatically estimate its parameters, human expertise to examine the partial correlogram of the time series is still required.

2.2 *Experimental Results*

2.2.1 Evaluation Setup

ARIMA is trained using a sliding window preceding the prediction period. The usage is measured every 15 minutes. Predictions are made for two horizons: 16 (4 hours) and 96 (24 hours). The objective of

using two prediction horizons is to examine how performance changes as a function of how far ahead in time the predictions are made. We run the test for (p, d, q) equal to (8, 1, 4), (8, 1, 8), and (4, 1, 4).

We test the methods accuracy in terms of Mean Absolute Percentage Error (MAPE). We calculate MAPE values considering either weekdays only or all-days.

2.2.2 Observations and Results

In Table 1, we investigate the performance of ARIMA (p=8, d=1, q=4) for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As can be seen, in this case, the historical data length has a little impact on the performance of the ARIMA. The prediction error is reasonably low and the small standard deviation shows a good concentration around the mean error. This can be concluded as a successful experiment.

Table 2 demonstrates the prediction of ARIMA (p=8, d=1, q=4) for data collected till 4pm. Predictions are for 1 to 5pm on the next day. For this case, ARIMA does not perform as well as previous case and given the relatively large standard deviation, we suggest applying another method. It is worthy to point out that ARIMA performs poorly for different historical data lengths.

Table 3 lists the prediction of ARIMA (p=8, d=1, q=4) for data collected till midnight. Predictions are for 1 to 5pm on the next day. Here, given the observed standard deviation and the errors, the prediction is completely unreliable. Roughly speaking, the error gets smaller as the size of the historical data grows.

The performance of ARIMA (p=8, d=1, q=4) for data collected till midnight is shown in Table 4. Predictions are for the entire next day. Again the performance is completely unreliable but shows an obvious correlation with the length of historical data, however, because of the high standard deviation we doubt that even larger historical data length will provide much improvement. Also keep in mind that predicting for the entire next day is a hard task and not many methods can provide a good performance for the task.

In Table 5, prediction results for ARIMA (p=8, d=1, q=8) for data collected till 1pm is listed. Predictions are for 1 to 5pm on the same day. This is another successful experiment where the error and standard deviation are low. This, of course, was predictable from Table 1, as increasing the moving average window size q, will not highly affect the result. It seems that during this time period the data is more stationary while it is not the case for other tested periods.

Table 6 is similar to Table 5 with difference that the prediction is for the next day. Obviously, the error will be increased. This is the same setup as Table 2 with q = 8 and we see the similar performance. Again we suggest applying another method given the standard deviation.

The predictions in Table 7 belong to ARIMA (p=8, d=1, q=8) for data collected till midnight. The predictions are for 1-5pm on the next day. Again, it is similar to Table 3 with q = 8. ARIMA performs poorly with high standard deviations which make it completely unreliable for this case.

Table 8 shows the performance of ARIMA (p=8, d=1, q=8) for data collected till midnight. Predictions are for the entire next day. Similar to Table 4, ARIMA is unreliable and performs poorly. We see some correlation between the historical data length and the error. Let us point out again that prediction for the entire next day is hard task which makes the performance more understandable.

Table 9 lists the result of ARIMA (p=4, d=1, q=4) for data collected till 1pm. Predictions are for 1 to 5pm on the same day. Similar to Tables 1 and 5, we see a good performance as the error and standard deviation are small.

The result for ARIMA (p=4, d=1, q=4) for data collected till 4pm is listed in Table 10. Predictions are for 1 to 5pm on the next day. Tables 2 and 6 consider the similar scenario with different parameters. The results are moderate and given the large standard deviation we suggest application of other methods.

In Table 11 predictions for ARIMA (p=4, d=1, q=4) for data collected till midnight are listed. Predictions are for 1 to 5pm on the next day. Similar to Tables 3 and 7 the results are highly erroneous which makes ARIMA unreliable for this case.

Table 12 lists predictions for ARIMA (p=4, d=1, q=4) for data collected till midnight. Predictions are for the next day. Similar to Tables 4 and 8, ARIMA performs poorly in this scenario. We, however, see a correlation between the historical data length and error as error gets smaller when the historical data length increases. Of course, note that prediction for the next day is a hard task and thus the poor performance is understandable.

2.3 *Conclusions and the Best Scenario*

Except the case where we predict the usage for 1 to 5pm on the same day given the data till 1pm, we do not see a good performance. Also, the high standard deviation in most cases degrades the performance further. In Tables 4, 8, and 12 we considered the prediction horizon of 96 as the forecasts were for the entire next day.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	1pm	96	16	5.52%	5.25745
10000	1pm	672	16	5.30%	5.07407
10000	1pm	1344	16	5.21%	4.73935
10000	1pm	2668	16	5.45%	4.8803
50000	1pm	96	16	5.11%	5.19884
50000	1pm	672	16	4.81%	4.87947
50000	1pm	1344	16	4.59%	4.43985
50000	1pm	2668	16	5.17%	4.87675
5000	1pm	96	16	5.78%	5.43791
5000	1pm	672	16	5.10%	4.6228
5000	1pm	1344	16	5.18%	4.4871
5000	1pm	2668	16	5.47%	4.87518
1000	1pm	96	16	7.28%	5.9427
1000	1pm	672	16	6.50%	5.49731
1000	1pm	1344	16	6.37%	5.16729
1000	1pm	2668	16	6.23%	5.011

Table- 1 Prediction using ARIMA (p=8, d=1, q=4) using data collected till 1pm. Predictions are for 1-5pm on the same day. Observation: Historical data length has minimal impact on error.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	4pm	96	16	21.02%	15.2428

10000	4pm	672	16	20.09%	15.352
10000	4pm	1344	16	19.55%	15.5598
10000	4pm	2668	16	20.06%	15.606
50000	4pm	96	16	20.93%	15.9033
50000	4pm	672	16	20.58%	15.647
50000	4pm	1344	16	19.82%	15.7027
50000	4pm	2668	16	20.23%	16.0069
5000	4pm	96	16	20.99%	15.883
5000	4pm	672	16	19.93%	15.4489
5000	4pm	1344	16	19.53%	15.155
5000	4pm	2668	16	19.60%	15.7025
1000	4pm	96	16	20.05%	15.4157
1000	4pm	672	16	19.30%	15.0097
1000	4pm	1344	16	18.98%	15.0457
1000	4pm	2668	16	18.12%	14.07

Table- 2 Prediction using ARIMA (p=8, d=1, q=4) using data collected till 4pm. Predictions are for 1-5pm on the next day. Observation: Historical data length has minimal impact on error.

Dataset	**Historical Data End Time**	**Historical Data Length**	**Prediction horizon**	**Error**	**STD**
10000	midnight	96	16	92.78%	40.1355
10000	midnight	672	16	50.53%	35.1079
10000	midnight	1344	16	36.10%	33.5052

10000	midnight	2668	16	55.47%	30.3345
50000	midnight	96	16	91.90%	36.9627
50000	midnight	672	16	54.49%	35.8546
50000	midnight	1344	16	36.08%	31.9492
50000	midnight	2668	16	47.56%	31.3532
5000	midnight	96	16	98.58%	36.9857
5000	midnight	672	16	46.35%	34.7817
5000	midnight	1344	16	40.74%	33.2495
5000	midnight	2668	16	46.03%	31.5302
1000	midnight	96	16	96.18%	36.3513
1000	midnight	672	16	72.95%	28.2842
1000	midnight	1344	16	55.61%	35.2161
1000	midnight	2668	16	33.88%	32.293

Table - 3 Prediction using ARIMA (p=8, d=1, q=4) using data collected till midnight. Predictions are for 1-5pm on the next day. Observation: Historical data length has an impact on error where error reduced with the historical data length, but started to increase after 1344.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	midnight	96	96	72.49%	48.1328
10000	midnight	672	96	37.82%	33.3033
10000	midnight	1344	96	27.75%	29.2857
10000	midnight	2668	96	39.78%	31.4074
50000	midnight	96	96	70.38%	46.931
50000	midnight	672	96	40.49%	35.162
50000	midnight	1344	96	27.43%	28.0922
50000	midnight	2668	96	34.29%	29.9903
5000	midnight	96	96	77.13%	48.7894
5000	midnight	672	96	34.55%	32.1632
5000	midnight	1344	96	30.19%	29.9647
5000	midnight	2668	96	34.18%	29.1112
1000	midnight	96	96	74.70%	49.7762
1000	midnight	672	96	53.95%	34.7203
1000	midnight	1344	96	42.37%	33.9517
1000	midnight	2668	96	26.06%	27.6971

Table - 4 Prediction using ARIMA (p=8, d=1, q=4) using data collected till midnight. Predictions are for the entire next day. Observations: Historical data length has an impact on error where error reduced with the historical data length, but started to increase after 1344.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	1pm	96	16	5.52%	5.30578
10000	1pm	672	16	5.30%	4.82379
10000	1pm	1344	16	5.21%	4.36545
10000	1pm	2668	16	5.45%	4.60258
50000	1pm	96	16	5.24%	5.30662
50000	1pm	672	16	4.75%	4.80891
50000	1pm	1344	16	4.39%	4.25855
50000	1pm	2668	16	4.64%	4.3318
1000	1pm	96	16	7.37%	6.54218
1000	1pm	672	16	6.26%	5.51318
1000	1pm	1344	16	5.85%	4.69973
1000	1pm	2668	16	5.80%	4.81965
5000	1pm	96	16	5.79%	5.47913
5000	1pm	672	16	4.92%	4.60589
5000	1pm	1344	16	4.82%	4.15078
5000	1pm	2668	16	4.90%	4.32754

Table - 5 Prediction using ARIMA (p=8, d=1, q=8) using data collected till 1pm. Predictions are for 1-5pm on the same day. Observation: Historical data length has minimal impact on error.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	4pm	96	16	21.02%	15.5017
10000	4pm	672	16	20.09%	15.5312
10000	4pm	1344	16	19.55%	15.4125
10000	4pm	2668	16	20.06%	15.6461
50000	4pm	96	16	20.50%	15.4762
50000	4pm	672	16	19.70%	15.8212
50000	4pm	1344	16	19.79%	15.6235
50000	4pm	2668	16	20.25%	16.0398
1000	4pm	96	16	19.69%	14.9747
1000	4pm	672	16	17.96%	14.2029
1000	4pm	1344	16	17.97%	14.0616
1000	4pm	2668	16	17.55%	13.4966
5000	4pm	96	16	20.56%	15.8834
5000	4pm	672	16	19.26%	15.0702
5000	4pm	1344	16	18.67%	14.8664
5000	4pm	2668	16	18.94%	14.8025

Table - 6 Prediction using ARIMA (p=8, d=1, q=8) using data collected till 4pm. Predictions are for 1-5pm on the next day. Observation: Historical data length has an impact on error where error reduced with the historical data length, but started to increase after 1344.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	midnight	96	16	92.78%	41.1341
10000	midnight	672	16	50.53%	33.9295
10000	midnight	1344	16	36.10%	30.3077
10000	midnight	2668	16	55.47%	32.0045
50000	midnight	96	16	57.05%	39.6999
50000	midnight	672	16	30.98%	28.1612
50000	midnight	1344	16	29.75%	29.3654
50000	midnight	2668	16	50.53%	32.3595
1000	midnight	96	16	79.96%	41.8902
1000	midnight	672	16	30.73%	30.6637
1000	midnight	1344	16	20.30%	24.4633
1000	midnight	2668	16	12.18%	8.90202
5000	midnight	96	16	76.90%	46.324
5000	midnight	672	16	36.83%	33.0557
5000	midnight	1344	16	25.97%	25.6469
5000	midnight	2668	16	29.87%	28.4339

Table - 7 Prediction using ARIMA (p=8, d=1, q=8) using data collected till midnight. Predictions are for 1-5pm on the next day. Observation: Historical data length has an impact on error where error reduced with the historical data length, but started to increase after 1344.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	midnight	96	96	72.49%	43.1124
10000	midnight	672	96	37.82%	31.5759
10000	midnight	1344	96	27.75%	26.2519
10000	midnight	2668	96	39.78%	28.1212
50000	midnight	96	96	43.55%	38.5676
50000	midnight	672	96	24.22%	24.2517
50000	midnight	1344	96	23.20%	25.0109
50000	midnight	2668	96	36.85%	30.9306
1000	midnight	96	96	62.79%	47.6491
1000	midnight	672	96	23.95%	26.4661
1000	midnight	1344	96	17.27%	20.8621
1000	midnight	2668	96	11.39%	8.89893
5000	midnight	96	96	60.03%	48.3662
5000	midnight	672	96	28.92%	29.2154
5000	midnight	1344	96	21.06%	21.8558
5000	midnight	2668	96	23.24%	24.4046

Table - 8 Prediction using ARIMA (p=8, d=1, q=8) using data collected till midnight. Predictions are for the entire next day. Observation: Historical data length has an impact on error where error reduced with the historical data length, but started to increase after 1344.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	1pm	96	16	5.38%	5.20374
10000	1pm	672	16	5.02%	4.97977
10000	1pm	1344	16	5.11%	4.81808
10000	1pm	2668	16	5.28%	4.86788
50000	1pm	96	16	5.08%	5.05438
50000	1pm	672	16	4.97%	4.88147
50000	1pm	1344	16	4.53%	4.47326
50000	1pm	2668	16	4.87%	4.77215
1000	1pm	96	16	7.25%	6.31933
1000	1pm	672	16	6.56%	5.32703
1000	1pm	1344	16	6.76%	5.4239
1000	1pm	2668	16	6.08%	4.92886
5000	1pm	96	16	5.90%	5.47175
5000	1pm	672	16	5.12%	4.85791
5000	1pm	1344	16	5.49%	5.03255
5000	1pm	2668	16	5.16%	4.68829

Table - 9 Prediction using ARIMA (p=4, d=1, q=4) using data collected till 1pm. Predictions are for 1-5pm on the same day. Observation: Historical data length has minimal impact on error.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	4pm	96	16	21.57%	15.6938
10000	4pm	672	16	20.83%	15.605
10000	4pm	1344	16	20.97%	15.3998
10000	4pm	2668	16	20.59%	15.7394
50000	4pm	96	16	21.29%	15.7668
50000	4pm	672	16	21.84%	16.4038
50000	4pm	1344	16	21.38%	16.5669
50000	4pm	2668	16	21.03%	16.2683
1000	4pm	96	16	20.27%	15.2883
1000	4pm	672	16	19.58%	14.8778
1000	4pm	1344	16	19.25%	14.5476
1000	4pm	2668	16	18.06%	13.8454
5000	4pm	96	16	21.27%	16.0044
5000	4pm	672	16	19.96%	15.5516
5000	4pm	1344	16	20.05%	15.3184
5000	4pm	2668	16	20.06%	15.7646

Table - 10 Prediction using ARIMA (p=4, d=1, q=4) using data collected till 4pm. Predictions are for 1-5pm on the next day. Observation: Historical data length has minimal impact on error.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	midnight	96	16	104.40%	36.877
10000	midnight	672	16	72.21%	28.8078
10000	midnight	1344	16	62.77%	27.0889
10000	midnight	2668	16	61.95%	25.7856
50000	midnight	96	16	102.29%	39.0521
50000	midnight	672	16	79.59%	37.7946
50000	midnight	1344	16	83.97%	53.5593
50000	midnight	2668	16	87.13%	49.5264
1000	midnight	96	16	94.94%	38.3191
1000	midnight	672	16	68.85%	32.2266
1000	midnight	1344	16	56.32%	31.6002
1000	midnight	2668	16	27.97%	28.4375
5000	midnight	96	16	106.99%	34.2861
5000	midnight	672	16	58.36%	36.5195
5000	midnight	1344	16	45.42%	31.9365
5000	midnight	2668	16	55.45%	30.7327

Table - 11 Prediction using ARIMA (p=4, d=1, q=4) using data collected till midnight. Predictions are for 1-5pm on the next day. Observation: Historical data length has an impact on error where error reduced with the historical data length.

Dataset	Historical Data End Time	Historical Data Length	Prediction horizon	Error	STD
10000	midnight	96	96	81.30%	51.9548
10000	midnight	672	96	53.11%	35.4542
10000	midnight	1344	96	45.88%	30.8323
10000	midnight	2668	96	44.35%	29.8024
50000	midnight	96	96	78.95%	52.6271
50000	midnight	672	96	57.88%	44.7204
50000	midnight	1344	96	64.09%	59.7205
50000	midnight	2668	96	66.07%	57.0723
1000	midnight	96	96	74.12%	50.1193
1000	midnight	672	96	51.97%	35.4874
1000	midnight	1344	96	41.58%	32.1552
1000	midnight	2668	96	21.71%	24.3078
5000	midnight	96	96	83.58%	49.9283
5000	midnight	672	96	44.14%	35.8596
5000	midnight	1344	96	34.74%	29.5404
5000	midnight	2668	96	40.87%	30.7995

Table - 12 Prediction using ARIMA (p=4, d=1, q=4) using data collected till midnight. Predictions are for the next day. Observation: Historical data length has an impact on error where error reduced with the historical data length.

3. *Static Models*

Let us start by providing a brief description of the considered static models.

3.1 *Static models for time series*

These consumption models are used as baseline models by utilities for determining what the consumption would have been for a particular curtailment period. Three baseline model algorithms are provided by the DDS Java library: California ISO **(CAISO)**, New York ISO **(NYISO)**, and Southern California Edison **(CASCE)**. These models do not require training and can be used as such.

Timeseries models require the KWh consumption values for recent time intervals to be passed in order to predict the subsequent time intervals. For e.g., the last 10 days of KWh values at 15 min intervals may be required to predict the next 24 hours of KWh values. The number of historical intervals required for prediction depends both on the model and the number of future intervals to predict. Timeseries models typically do not offer accurate predictions for more than 24hrs into the future.

3.2 *Experimental Results*

3.2.1 Evaluation setup

We test the methods accuracy in terms of Mean Absolute Percentage Error (MAPE). We calculate MAPE values considering either weekdays only or all-days. The usage is measured every 15 minutes. Predictions are made for two horizons: 16 (4 hours) and 96 (24 hours).

3.2.2 CAISO: Observations and Results

Let us start by analyzing the performance of CAISO. In Table 13, we investigate the performance of CAISO for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As can be seen, in this case, the historical data length has a little impact on the performance of the CAISO. The prediction error is not low and given the large standard deviation the method is not reliable.

Table 14 demonstrates the prediction for data collected till 4pm. Predictions are for 1 to 5pm on the next day. For this case, CAISO performs similar to the previous case, and thus it is unreliable.

Table 15 lists the prediction for data collected till midnight. Predictions are for 1 to 5pm on the next day. Again the performance is similar to the previous cases.

The performance for data collected till midnight is shown in Table 16. Predictions are for the entire next day. This time, compared with the previous cases, CAISO performs relatively well. Note that predicting

for the entire next day is a hard task and not many methods can provide a good performance for the task. Thus we believe that CAISO can be a candidate for this case.

3.2.3 NYISO: Observations and Results

Table 17 lists the performance of NYISO for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As shown, NYISO performs better than CAISO and the result is acceptable. The only point of concern is the relatively high standard deviation.

Table 18 shows the prediction for data collected till 4pm. Predictions are for 1 to 5pm on the next day. For this case, NYISO performs surprisingly well and much better than CAISO. Given the low standard deviation it seems to be a good candidate for this scenario.

Table 19 demonstrates the prediction for data collected till midnight. Predictions are for 1 to 5pm on the next day. Again, NYISO performs well and outperforms CAISO. Note that the standard deviation is also small which encourages the application of NYISO for this scenario.

The performance for data collected till midnight is shown in Table 20. Predictions are for the entire next day. Prediction for the entire next day is a hard task and NYISO performs superbly with small error and small standard deviation.

3.2.4 CASCE: Observations and Results

Finally, we present the results on the performance of CASCE. Table 21 lists the performance of CASCE for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As shown, CASCE outperforms other methods (compared with Tables 1 and 5) with both small error and small standard deviation and seems to be the best candidate for this case.

Table 22 shows the prediction for data collected till 4pm. Predictions are for 1 to 5pm on the next day. For this case, CASCE provides slightly worse error compared with NYISO (Table 6). However, CASCE has a smaller standard deviation which shows it has a more stable performance.

3.3 ***Conclusion and the Best Scenario***

Based on the results provided in Tables 13-22, CASCE seems to be the best candidate. Of course, we do not have a result on its performance for two of the cases. NYISO, however, performs really well in both of those cases. We believe both CASCE and NYISO offer good results and should be applied. CAISO, however, has a poor performance in all scenarios and should be disregarded.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	1pm	16	33.3634	34.4343
5000	1pm	16	33.4297	35.1607
10000	1pm	16	33.0073	34.4503
50000	1pm	16	33.48	35.2181

Table - 13 Prediction using CAISO using data collected till 1pm. Predictions are for 1-5pm on the same day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	4pm	16	33.9416	34.5399
5000	4pm	16	34.0318	35.2927
10000	4pm	16	33.6219	34.6583
50000	4pm	16	34.1123	35.4524

Table - 14 Prediction using CAISO using data collected till 4pm. Predictions are for 1-5pm on the same day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	midnight	16	33.0807	34.1168
5000	midnight	16	33.1082	34.7365
10000	midnight	16	32.712	34.0565
50000	midnight	16	33.2206	34.8759

Table - 15 Prediction using CAISO using data collected till midnight. Predictions are for 1-5pm on the next day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	midnight	96	23.2378	24.7279
5000	midnight	96	23.1314	24.7182
10000	midnight	96	22.9432	24.4819
50000	midnight	96	23.1041	24.8407

Table - 16 Prediction using CAISO using data collected till midnight. Predictions are for the entire next day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	1pm	16	15.9035%	17.5917
5000	1pm	16	16.0459%	18.2726
10000	1pm	16	15.6277%	17.6772
50000	1pm	16	16.0178%	17.7671

Table - 17 Prediction using NYISO using data collected till 1pm. Predictions are for 1-5pm on the same day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	4pm	16	23.636%	15.7115
5000	4pm	16	24.0119%	16.1745
10000	4pm	16	23.6841%	15.7357
50000	4pm	16	23.9939%	15.9141

Table - 18 Prediction using NYISO using data collected till 4pm. Predictions are for 1-5pm on the next day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	midnight	16	18.1672%	16.9
5000	midnight	16	18.5375%	17.6675
10000	midnight	16	18.1639%	17.0609
50000	midnight	16	18.4646%	17.128

Table - 19 Prediction using NYISO using data collected till midnight. Predictions are for 1-5pm on the next day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	midnight	96	10.9272	11.6745
5000	midnight	96	10.8002	11.9011
10000	midnight	96	10.6815	11.6526
50000	midnight	96	10.7099	11.683

Table - 20 Prediction using NYISO using data collected till midnight. . Predictions are for the entire next day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	1pm	16	11.0602	9.52635
5000	1pm	16	11.2396	9.86244
10000	1pm	16	10.9754	9.36192
50000	1pm	16	11.2842	9.79234

Table - 21 Prediction using CASCE using data collected till 1pm. Predictions are for 1-5pm on the same day.

Dataset	Historical Data End Time	prediction horizon	Error (%)	STD
1000	4pm	16	25.6342	12.8257
5000	4pm	16	25.956	12.7952
10000	4pm	16	25.6966	12.7372
50000	4pm	16	25.9489	12.7282

Table - 22 Prediction using CASCE using data collected till 4pm. Predictions are for 1-5pm on the next day

4. *Data Driven/Dynamic Models*

Let us start by providing a brief description of the data driven/dynamic models.

4.1 *Data-driven/Dynamic Models*

Data-driven dynamic models use machine learning to train the model using a set of feature vectors provided for each consumption interval. For e.g., a feature vector for a KWh consumption for a particular customer and a particular time interval could be customer type, customer zipcode, outside temperature, and day of the week. Some of the feature vectors may change rarely (e.g. customer type and zipcode may not change for a given customer) while others may change more often (e.g. outside temperature may change every our). Such models often improve in accuracy as larger training datasets are available. We use the Regression Tree Algorithm for training the data-driven, dynamic model, and making predictions.

In linear regression, a real-valued variable Y (e.g., electric consumption) is modeled as a linear function of a real-valued variable X, plus noise: $Y = \beta_0 + \beta_1 X + \varepsilon$. In case of multiple variables having an additive effect on Y, linear regression can still be applied as follows: $Y = \beta_0 + \beta^T X + \varepsilon$, where X denotes a vector containing the values of variables X_1, X_2, …, X_k. When many variables interact in complicated, nonlinear ways, assembling a linear model can be very difficult. In such cases it might be better to divide the space into smaller regions where interactions are simple enough to be adequately modeled by simple models.

A regression tree (RT) model is used to model such complex data (i.e., several real-valued and/or categorical features) that cannot be effectively modeled by linear regression. An RT model is "learned" by recursively partitioning the training data into smaller regions until they can be represented by a constant or a linear model. The recursion is completed when features at a node are all associated with the same target variable value, or when splitting does not enhance the prediction. At the end, each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf. We refer to this model as WEKA as it uses the WEKA java library.

4.2 *Experimental Results*

4.2.1 Evaluation Setup

We test the methods accuracy in terms of Mean Absolute Percentage Error (MAPE). We calculate MAPE values considering either weekdays only or all-days. The usage is measured every 15 minutes. Predictions are made for two horizons: 16 (4 hours) and 96 (24 hours). We test the methods accuracy in terms of Mean Absolute Percentage Error (MAPE). We repeat the experiments 8 times, each time using different features as an input for WEKA. Specifically, we use the following setup of features:

First Setup: Time of the day, day of the week and consumption.

Second Setup: Fact that if it's a holiday or not (0/1) and consumption.

Third Setup: Time of the day and consumption.

Fourth Setup: The day of the week and consumption.

Fifth Setup: Only consumption.

Sixth Setup: Day of week, time of day, temperature from SUS dataset and consumption.

Seventh Setup: Temperature from underground dataset and consumption.

Eighth Setup: Temperature from SUS dataset and consumption.

4.2.2 Observations and Results

First setup. Let us start by considering the time of the day, day of the week, and consumption as features. In Table 23, we investigate the performance of WEKA for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As can be seen, in this case, WEKA performs really well with small error rate and standard deviation. The result also has some correlation with the historical data length.

Table 24 demonstrates the prediction for data collected till 4pm. Predictions are for 1 to 5pm on the next day. WEKA again performs pretty well with small error and standard deviation. Of course, the standard deviation is increased compared to the previous case.

Table 25 lists the prediction for data collected till midnight. Predictions are for 1 to 5pm on the next day. Similar to previous cases, WEKA performs really well.

The performance for data collected till midnight where the predictions are for the entire next day is shown in Table 26. This time, compared with the previous cases, WEKA performs a bit worse. However, it still has a relatively low standard deviation.

Second setup. As for the second round of testing, we consider whether it is a holiday or not and consumption amount as features. As shown in Table 27, we investigate the performance of WEKA for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As can be seen, in this case, WEKA performs really well with small error rate and standard deviation. The performance is slightly better than Table 23 as the standard deviation is a bit smaller.

Table 28 demonstrates the prediction for data collected till 4pm. Predictions are for 1 to 5pm on the next day. WEKA again performs pretty well with small error and standard deviation. Of course, the standard deviation is increased compared to the previous case. The result is again better than Table 2 with smaller error and standard deviation.

Table 29 lists the prediction for data collected till midnight. Predictions are for 1 to 5pm on the next day. Similar to previous cases, WEKA performs well and better than the previous setup shown in Table 25.

The performance for data collected till midnight where the predictions are for the entire next day is shown in Table 30. This time, compared with the previous cases, WEKA performs a bit worse. However, it still has a relatively low standard deviation. Also, it performs similar to the setup for Table 4.

Third setup. For the third round of testing, we consider time of the day and consumption as features. Table 31 demonstrates the performance of WEKA for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As can be seen, in this case, WEKA performs well with small error rate and standard deviation. The performance is slightly worse than Tables 1 and 5.

Table 32 shows the prediction for data collected till 4pm. Predictions are for 1 to 5pm on the next day. WEKA again performs well with small error and standard deviation, and we saw in previous setups, the standard deviation is increased compared to the previous case. The result is slightly worse than Tables 2 and 6 with bigger error and standard deviation.

In Table 33, we list the prediction for data collected till midnight. Predictions are for 1 to 5pm on the next day. Similar to previous cases, WEKA performs well and slightly worse than the previous setups shown in Tables 35 and 39.

The performance for data collected till midnight where the predictions are for the entire next day is shown in Table 34. This time, compared with the previous cases, WEKA performs a bit worse. However, it still has a relatively low standard deviation. Also, it performs similar to the setups for Tables 4 and 8.

Fourth setup. For the fourth round of testing, we consider the day of the week and consumption as features. Table 35 shows the performance of WEKA for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As shown, in this case, WEKA performs well with small error rate and standard deviation. The performance is similar to Table 5 and better than Tables 1 and 9.

Table 36 shows the prediction for data collected till 4pm. Predictions are for 1 to 5pm on the next day. WEKA again performs well with small error and standard deviation, and we saw in previous setups, the standard deviation is increased compared to the previous case. The result is similar to Table 6 and slightly better than Tables 2 and 10.

In Table 37, we list the prediction for data collected till midnight. Predictions are for 1 to 5pm on the next day. Similar to previous cases, WEKA performs well and similar to the result of the second setup.

The performance for data collected till midnight where the predictions are for the entire next day is shown in Table 38. This time, compared with the previous cases, WEKA performs a bit worse. However, it still has a relatively low standard deviation. Also, it performs similar to the second setups in Table 8 and better than others shown in Tables 36 and 34.

Fifth setup. We use the consumption for the fourth round of testing. Table 39 shows the performance of WEKA for data collected till 1pm. Predictions are made for 1 to 5pm on the same day. As shown, in this

case, WEKA performs well with small error rate and standard deviation. The performance is similar to Table 5 and better than Tables 1 and 9.

Table 40 shows the prediction for data collected till 4pm. Predictions are for 1 to 5pm on the next day. WEKA again performs well with small error and standard deviation, and we saw in previous setups, the standard deviation is increased compared to the previous case. The result is slightly worse than Tables 2 and 6 with bigger error and standard deviation.

In Table 41, we list the prediction for data collected till midnight. Predictions are for 1 to 5pm on the next day. Similar to previous cases, WEKA performs well and slightly worse than the previous setups shown in Tables 3 and 7.

The performance for data collected till midnight where the predictions are for the entire next day is shown in Table 12. This time, compared with the previous cases, WEKA performs a bit worse. However, it still has a relatively low standard deviation. Also, it performs similar to the setups for Tables 4 and 8.

4.3 ***Conclusion and the Best Scenario***

The best performance is achieved under setups 2 and 4 with similar outcomes. We believe the reason is due to the fact that except consumption which must be used in all setups, whether it's a holiday or not (0/1) the day of the week are have a huge impact and correlation with the consumption behavior. Thus these setups benefit greatly from these features and can outperform other scenarios.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	1pm	96	16	21.91%	9.47996
5000	1pm	96	16	22.00%	9.496932
10000	1pm	96	16	22.27%	9.838236
50000	1pm	96	16	22.24%	9.534314
1000	1pm	672	16	24.33%	10.46823
5000	1pm	672	16	24.23%	9.473969
10000	1pm	672	16	24.36%	9.858872
50000	1pm	672	16	24.68%	9.947804
1000	1pm	1344	16	22.71%	10.42013
5000	1pm	1344	16	22.69%	9.575696
10000	1pm	1344	16	22.94%	9.397282
50000	1pm	1344	16	23.09%	9.49598
1000	1pm	2688	16	23.43%	10.86819
5000	1pm	2688	16	22.97%	10.08587
10000	1pm	2688	16	23.32%	9.79219
50000	1pm	2688	16	23.66%	9.84385

Table - 23 Prediction using WEKA regression tree based model. Data collected till 1pm. Predictions are for 1-5pm on the same day. Time of the day, day of the week and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	4pm	96	16	15.89%	11.5783
5000	4pm	96	16	16.09%	11.81916
10000	4pm	96	16	16.00%	11.70125
50000	4pm	96	16	16.13%	11.82654
1000	4pm	672	16	17.31%	13.97956
5000	4pm	672	16	17.35%	13.57357
10000	4pm	672	16	17.50%	13.61791
50000	4pm	672	16	17.52%	13.63504
1000	4pm	1344	16	17.00%	13.53416
5000	4pm	1344	16	17.14%	12.82273
10000	4pm	1344	16	17.24%	13.34262
50000	4pm	1344	16	17.13%	13.33956
1000	4pm	2688	16	17.00%	13.43073
5000	4pm	2688	16	17.19%	13.26069
10000	4pm	2688	16	17.20%	13.20824
50000	4pm	2688	16	17.18%	13.19717

Table - 24 Prediction using WEKA regression tree based model. Data collected till 4pm. Predictions are for 1-5pm on the next day. Time of the day, day of the week and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	16	22.49%	13.27954
1000	midnight	2688	16	21.85%	12.99495
1000	midnight	672	16	23.55%	13.07255
1000	midnight	96	16	19.42%	11.05705
5000	midnight	1344	16	19.16%	11.91408
5000	midnight	2688	16	18.07%	12.00959
5000	midnight	672	16	19.27%	12.07956
5000	midnight	96	16	15.81%	10.09456
10000	midnight	1344	16	18.31%	12.1647
10000	midnight	2688	16	17.88%	12.03965
10000	midnight	672	16	19.03%	12.06737
10000	midnight	96	16	15.59%	10.20111
50000	midnight	1344	16	18.78%	11.84032
50000	midnight	2688	16	18.52%	12.09009
50000	midnight	672	16	19.93%	12.30951
50000	midnight	96	16	16.22%	10.31267

Table - 25 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for 1-5pm on the same day. Time of the day, day of the week and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	96	35.19%	24.87614
1000	midnight	2688	96	35.26%	25.35585
1000	midnight	672	96	34.66%	24.2702
1000	midnight	96	96	36.61%	27.34118
5000	midnight	1344	96	35.72%	24.92533
5000	midnight	2688	96	35.76%	25.18041
5000	midnight	672	96	36.06%	25.21436
5000	midnight	96	96	37.46%	27.47662
10000	midnight	1344	96	35.17%	24.6191
10000	midnight	2688	96	35.44%	25.08155
10000	midnight	672	96	35.51%	24.96007
10000	midnight	96	96	37.06%	27.28224
50000	midnight	1344	96	36.07%	25.29031
50000	midnight	2688	96	35.38%	24.68242
50000	midnight	672	96	35.48%	24.37377
50000	midnight	96	96	37.05%	26.988

Table - 26 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for entire next day. Time of the day, day of the week and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	1pm	1344	16	21.29%	8.192519
1000	1pm	2688	16	22.05%	8.818209
1000	1pm	672	16	22.87%	8.422952
1000	1pm	96	16	20.91%	8.159015
5000	1pm	1344	16	21.65%	8.19814
5000	1pm	2688	16	21.84%	8.736939
5000	1pm	672	16	23.24%	8.210798
5000	1pm	96	16	21.04%	8.259507
10000	1pm	1344	16	21.92%	8.082223
10000	1pm	2688	16	22.29%	8.570773
10000	1pm	672	16	23.39%	8.724667
10000	1pm	96	16	21.05%	8.251776
50000	1pm	1344	16	22.05%	8.122791
50000	1pm	2688	16	22.58%	8.56627
50000	1pm	672	16	23.72%	8.820286
50000	1pm	96	16	21.15%	8.116361

Table - 27 Prediction using WEKA regression tree based model. Data collected till 1pm. Predictions are for 1-5pm. Fact that if it's a holiday or not (0/1) and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	4pm	1344	16	14.70%	11.06494
1000	4pm	2688	16	14.67%	10.91932
1000	4pm	672	16	14.92%	11.38028
1000	4pm	96	16	14.44%	10.79366
5000	4pm	1344	16	15.20%	11.35466
5000	4pm	2688	16	15.22%	11.68216
5000	4pm	672	16	15.25%	11.82788
5000	4pm	96	16	14.81%	11.33195
10000	4pm	1344	16	15.28%	11.93976
10000	4pm	2688	16	15.22%	11.61752
10000	4pm	672	16	15.43%	11.98513
10000	4pm	96	16	14.78%	11.29959
50000	4pm	1344	16	15.10%	11.77166
50000	4pm	2688	16	15.18%	11.62019
50000	4pm	672	16	15.41%	11.92358
50000	4pm	96	16	14.83%	11.35153

Table - 28 Prediction using WEKA regression tree based model. Data collected till 4pm. Predictions are for 1-5pm next day. Fact that if it's a holiday or not (0/1) and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	16	21.30%	11.71353
1000	midnight	2688	16	20.49%	11.28697
1000	midnight	672	16	22.48%	11.73551
1000	midnight	96	16	19.42%	11.05705
5000	midnight	1344	16	17.76%	10.50066
5000	midnight	2688	16	16.77%	10.43699
5000	midnight	672	16	17.67%	10.59934
5000	midnight	96	16	15.81%	10.09456
10000	midnight	1344	16	16.80%	10.65841
10000	midnight	2688	16	16.54%	10.53092
10000	midnight	672	16	17.61%	10.68964
10000	midnight	96	16	15.59%	10.20111
50000	midnight	1344	16	17.32%	10.31409
50000	midnight	2688	16	17.21%	10.64543
50000	midnight	672	16	18.63%	11.05855
50000	midnight	96	16	16.22%	10.31267

Table - 29 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for 1-5pm next day. Fact that if it's a holiday or not (0/1) and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	96	35.50%	25.23891
1000	midnight	2688	96	35.74%	25.93429
1000	midnight	672	96	35.44%	25.26434
1000	midnight	96	96	36.61%	27.34118
5000	midnight	1344	96	36.29%	25.63251
5000	midnight	2688	96	36.26%	25.7553
5000	midnight	672	96	36.79%	26.35646
5000	midnight	96	96	37.46%	27.47662
10000	midnight	1344	96	35.81%	25.4564
10000	midnight	2688	96	35.96%	25.6933
10000	midnight	672	96	36.10%	25.67572
10000	midnight	96	96	37.06%	27.28224
50000	midnight	1344	96	36.67%	26.01537
50000	midnight	2688	96	35.90%	25.29375
50000	midnight	672	96	36.00%	24.97682
50000	midnight	96	96	37.05%	26.988

Table - 30 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for entire next day. Fact that if it's a holiday or not (0/1) and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	1pm	1344	16	22.84%	10.03395
1000	1pm	2688	16	23.52%	10.01211
1000	1pm	672	16	24.10%	9.465216
1000	1pm	96	16	20.91%	8.146486
5000	1pm	1344	16	22.59%	9.435801
5000	1pm	2688	16	22.92%	9.113036
5000	1pm	672	16	23.87%	8.794082
5000	1pm	96	16	21.09%	8.275301
10000	1pm	1344	16	22.70%	9.201586
10000	1pm	2688	16	23.39%	9.105333
10000	1pm	672	16	23.89%	9.271537
10000	1pm	96	16	21.12%	8.270486
50000	1pm	1344	16	22.93%	9.341268
50000	1pm	2688	16	23.68%	9.019669
50000	1pm	672	16	24.26%	9.376266
50000	1pm	96	16	21.16%	8.124619

Table - 31 Prediction using WEKA regression tree based model. Data collected till 1pm. Predictions are for 1-5pm. Time of the day and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	4pm	1344	16	17.75%	12.97035
1000	4pm	2688	16	19.29%	12.9578
1000	4pm	672	16	17.34%	12.53618
1000	4pm	96	16	14.93%	11.0199
5000	4pm	1344	16	17.71%	12.31851
5000	4pm	2688	16	18.79%	12.38613
5000	4pm	672	16	17.04%	12.27516
5000	4pm	96	16	14.95%	11.33343
10000	4pm	1344	16	17.43%	12.4634
10000	4pm	2688	16	18.71%	12.11159
10000	4pm	672	16	17.14%	12.29693
10000	4pm	96	16	14.95%	11.31747
50000	4pm	1344	16	17.52%	12.53144
50000	4pm	2688	16	18.79%	12.25925
50000	4pm	672	16	17.22%	12.34408
50000	4pm	96	16	14.98%	11.35637

Table - 32 Prediction using WEKA regression tree based model. Data collected till 4pm. Predictions are for 1-5pm next day. Time of the day and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	16	22.37%	12.90158
1000	midnight	2688	16	23.06%	12.26313
1000	midnight	672	16	23.19%	12.12032
1000	midnight	96	16	19.42%	11.05705
5000	midnight	1344	16	19.45%	11.56384
5000	midnight	2688	16	19.18%	11.56694
5000	midnight	672	16	18.54%	11.06639
5000	midnight	96	16	15.81%	10.09456
10000	midnight	1344	16	18.50%	11.88517
10000	midnight	2688	16	19.10%	11.64302
10000	midnight	672	16	18.36%	11.14612
10000	midnight	96	16	15.59%	10.20111
50000	midnight	1344	16	19.07%	11.55211
50000	midnight	2688	16	19.63%	11.61337
50000	midnight	672	16	19.29%	11.46545

Table - 33 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for 1-5pm next day. Time of the day and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	96	35.48%	25.31526
1000	midnight	2688	96	35.29%	25.27351
1000	midnight	672	96	34.71%	23.92261
1000	midnight	96	96	36.61%	27.34118
5000	midnight	1344	96	35.67%	24.36021
5000	midnight	2688	96	35.26%	24.00483
5000	midnight	672	96	36.25%	25.25276
5000	midnight	96	96	37.46%	27.47662
10000	midnight	1344	96	35.10%	24.13393
10000	midnight	2688	96	34.92%	23.93089
10000	midnight	672	96	35.68%	24.96963
10000	midnight	96	96	37.06%	27.28224
50000	midnight	1344	96	35.85%	24.60201
50000	midnight	2688	96	34.94%	23.62848
50000	midnight	672	96	35.64%	24.37616
50000	midnight	96	96	37.05%	26.988

Table - 34 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for entire next day. Time of the day and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	1pm	1344	16	21.29%	8.192519
1000	1pm	2688	16	22.05%	8.818209
1000	1pm	672	16	22.90%	8.415583
1000	1pm	96	16	20.91%	8.159015
5000	1pm	1344	16	21.65%	8.19814
5000	1pm	2688	16	21.84%	8.736939
5000	1pm	672	16	23.24%	8.210798
5000	1pm	96	16	21.04%	8.259507
10000	1pm	1344	16	21.92%	8.082223
10000	1pm	2688	16	22.29%	8.570773
10000	1pm	672	16	23.39%	8.724667
10000	1pm	96	16	21.05%	8.251776
50000	1pm	1344	16	22.05%	8.122791
50000	1pm	2688	16	22.58%	8.56627
50000	1pm	672	16	23.72%	8.820286
50000	1pm	96	16	21.15%	8.116361

Table - 35 Prediction using WEKA regression tree based model. Data collected till 1pm. Predictions are for 1-5pm same day. The day of the week and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	4pm	1344	16	14.70%	11.06494
1000	4pm	2688	16	14.66%	10.92073
1000	4pm	672	16	14.94%	11.36931
1000	4pm	96	16	14.42%	10.80886
5000	4pm	1344	16	15.20%	11.35466
5000	4pm	2688	16	15.22%	11.68216
5000	4pm	672	16	15.25%	11.82788
5000	4pm	96	16	14.81%	11.33195
10000	4pm	1344	16	15.28%	11.93976
10000	4pm	2688	16	15.22%	11.61752
10000	4pm	672	16	15.43%	11.98513
10000	4pm	96	16	14.78%	11.29959
50000	4pm	1344	16	15.10%	11.77166
50000	4pm	2688	16	15.18%	11.62019
50000	4pm	672	16	15.41%	11.92358
50000	4pm	96	16	14.83%	11.35153

Table - 36 Prediction using WEKA regression tree based model. Data collected till 4pm. Predictions are for 1-5pm next day. The day of the week and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	16	21.26%	11.76309
1000	midnight	2688	16	20.49%	11.28697
1000	midnight	672	16	22.35%	11.76675
1000	midnight	96	16	19.42%	11.05705
5000	midnight	1344	16	17.76%	10.50066
5000	midnight	2688	16	16.77%	10.43699
5000	midnight	672	16	17.67%	10.59934
5000	midnight	96	16	15.81%	10.09456
10000	midnight	1344	16	16.80%	10.65841
10000	midnight	2688	16	16.54%	10.53092
10000	midnight	672	16	17.61%	10.68964
10000	midnight	96	16	15.59%	10.20111
50000	midnight	1344	16	17.32%	10.31409
50000	midnight	2688	16	17.21%	10.64543
50000	midnight	672	16	18.63%	11.05855
50000	midnight	96	16	16.22%	10.31267

Table - 37 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for 1-5pm next day. The day of the week and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	96	35.60%	25.34051
1000	midnight	2688	96	35.74%	25.93429
1000	midnight	672	96	35.11%	24.8654
1000	midnight	96	96	36.61%	27.34118
5000	midnight	1344	96	36.29%	25.63251
5000	midnight	2688	96	36.26%	25.7553
5000	midnight	672	96	36.79%	26.35646
5000	midnight	96	96	37.46%	27.47662
10000	midnight	1344	96	35.81%	25.4564
10000	midnight	2688	96	35.96%	25.6933
10000	midnight	672	96	36.10%	25.67572
10000	midnight	96	96	37.06%	27.28224
50000	midnight	1344	96	36.67%	26.01537
50000	midnight	2688	96	35.90%	25.29375
50000	midnight	672	96	36.00%	24.97682
50000	midnight	96	96	37.05%	26.988

Table - 38 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for entire next day. The day of the week and consumption were used as features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
10000	1pm	96	16	21.05%	8.2518
10000	1pm	672	16	23.39%	8.7247
10000	1pm	1344	16	21.92%	8.0822
10000	1pm	2668	16	22.30%	8.5708
50000	1pm	96	16	21.05%	8.2518
50000	1pm	672	16	23.39%	8.7247
50000	1pm	1344	16	21.92%	8.0822
50000	1pm	2668	16	22.30%	8.5708
5000	1pm	96	16	21.04%	8.2595
5000	1pm	672	16	23.24%	8.2108
5000	1pm	1344	16	21.65%	8.1987
5000	1pm	2668	16	21.84%	8.7369
1000	1pm	96	16	20.91%	8.159
1000	1pm	672	16	22.87%	8.423
1000	1pm	1344	16	21.29%	8.1925
1000	1pm	2668	16	22.05%	8.8182

Table - 39 Prediction using WEKA regression tree based model. Data collected till 1pm. Predictions are for 1-5pm same day. Consumption was used as the feature.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
10000	4pm	96	16	14.78%	11.3
10000	4pm	672	16	15.43%	11.985
10000	4pm	1344	16	15.28%	11.94
10000	4pm	2668	16	15.22%	11.618
50000	4pm	96	16	14.78%	11.3
50000	4pm	672	16	15.43%	11.958
50000	4pm	1344	16	15.28%	11.94
50000	4pm	2668	16	15.22%	11.618
5000	4pm	96	16	14.81%	11.332
5000	4pm	672	16	15.25%	11.828
5000	4pm	1344	16	15.20%	11.355
5000	4pm	2668	16	15.22%	11.682
1000	4pm	96	16	14.44%	10.794
1000	4pm	672	16	14.92%	11.38
1000	4pm	1344	16	14.70%	11.065
1000	4pm	2668	16	14.67%	10.919

Table - 40 Prediction using WEKA regression tree based model. Data collected till 4pm. Predictions are for 1-5pm next day. Consumption was used as the feature.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
10000	midnight	96	16	15.59%	10.201
10000	midnight	672	16	17.61%	10.69
10000	midnight	1344	16	16.80%	10.658
10000	midnight	2668	16	16.54%	10.531
50000	midnight	96	16	15.59%	10.201
50000	midnight	672	16	17.61%	10.69
50000	midnight	1344	16	16.80%	10.658
50000	midnight	2668	16	16.54%	10.531
5000	midnight	96	16	15.81%	10.095
5000	midnight	672	16	17.67%	10.599
5000	midnight	1344	16	17.76%	10.501
5000	midnight	2668	16	16.77%	10.437
1000	midnight	96	16	19.42%	11.057
1000	midnight	672	16	22.35%	11.767
1000	midnight	1344	16	21.00%	11.714
1000	midnight	2668	16	20.49%	11.287

Table - 41 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for 1-5pm next day. Consumption was used as the feature.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
10000	midnight	96	96	37.06%	27.282
10000	midnight	672	96	36.10%	25.676
10000	midnight	1344	96	35.81%	25.456
10000	midnight	2668	96	35.96%	25.693
50000	midnight	96	96	37.06%	27.282
50000	midnight	672	96	36.10%	25.676
50000	midnight	1344	96	35.81%	25.456
50000	midnight	2668	96	35.96%	25.693
5000	midnight	96	96	37.46%	27.477
5000	midnight	672	96	36.79%	26.356
5000	midnight	1344	96	36.29%	25.633
5000	midnight	2668	96	36.26%	25.755
1000	midnight	96	96	36.61%	27.341
1000	midnight	672	96	35.11%	24.865
1000	midnight	1344	96	35.50%	25.239
1000	midnight	2668	96	35.74%	25.934

Table - 42 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for entire next day. Consumption was used as the feature.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	1pm	1344	16	44.63%	20.67221
1000	1pm	2688	16	40.33%	20.62814
1000	1pm	672	16	47.77%	17.70505
1000	1pm	96	16	36.13%	18.34304
5000	1pm	1344	16	43.95%	20.0003
5000	1pm	2688	16	40.01%	18.95306
5000	1pm	672	16	46.80%	17.46012
5000	1pm	96	16	31.27%	15.90184
10000	1pm	1344	16	43.28%	20.17512
10000	1pm	2688	16	40.57%	19.06241
10000	1pm	672	16	46.34%	17.08246
10000	1pm	96	16	32.27%	16.31547
50000	1pm	1344	16	44.06%	20.23095
50000	1pm	2688	16	40.85%	19.12722
50000	1pm	672	16	46.65%	17.30391
50000	1pm	96	16	32.98%	17.06843

Table - 43 Prediction using WEKA regression tree based model. Data collected till 1pm. Predictions are for 1-5pm same day. Day of week, time of day, temperature from SUS dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	4pm	1344	16	44.01%	21.07414
1000	4pm	2688	16	39.69%	20.44506
1000	4pm	672	16	45.65%	20.3694
1000	4pm	96	16	27.54%	21.64107
5000	4pm	1344	16	42.36%	21.36808
5000	4pm	2688	16	39.63%	19.56202
5000	4pm	672	16	43.39%	21.37616
5000	4pm	96	16	23.65%	19.50353
10000	4pm	1344	16	42.02%	20.88487
10000	4pm	2688	16	38.64%	19.98839
10000	4pm	672	16	42.97%	21.00427
10000	4pm	96	16	23.53%	19.47614
50000	4pm	1344	16	43.39%	20.56984
50000	4pm	2688	16	39.73%	19.68958

50000	4pm	672	16	43.36%	21.26466
50000	4pm	96	16	23.70%	19.67292

Table - 44 Prediction using WEKA regression tree based model. Data collected till 4pm. Predictions are for 1-5pm next day. Day of week, time of day, temperature from SUS dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	16	38.84%	22.09021
1000	midnight	2688	16	36.62%	20.52157
1000	midnight	672	16	36.04%	21.57556
1000	midnight	96	16	19.41%	11.05777
5000	midnight	1344	16	39.00%	22.53287
5000	midnight	2688	16	35.31%	19.79621
5000	midnight	672	16	31.96%	23.02967
5000	midnight	96	16	16.12%	10.0977
10000	midnight	1344	16	38.41%	22.49173
10000	midnight	2688	16	36.95%	19.94398
10000	midnight	672	16	31.07%	21.85661
10000	midnight	96	16	15.88%	10.19156
50000	midnight	1344	16	39.35%	22.56821
50000	midnight	2688	16	37.05%	19.69321
50000	midnight	672	16	32.27%	22.6322
50000	midnight	96	16	16.50%	10.29453

Table - 45 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for 1-5pm next day. Day of week, time of day, temperature from SUS dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	96	41.03%	29.01304
1000	midnight	2688	96	41.00%	31.0209
1000	midnight	672	96	38.66%	27.60361
1000	midnight	96	96	36.63%	27.36418
5000	midnight	1344	96	40.87%	27.3627
5000	midnight	2688	96	38.34%	26.75719
5000	midnight	672	96	39.06%	27.74689
5000	midnight	96	96	37.75%	27.61596
10000	midnight	1344	96	40.55%	27.53729
10000	midnight	2688	96	39.39%	26.83699
10000	midnight	672	96	37.84%	26.4348
10000	midnight	96	96	37.36%	27.48635
50000	midnight	1344	96	41.08%	27.97384
50000	midnight	2688	96	39.20%	27.18065
50000	midnight	672	96	38.82%	27.2814
50000	midnight	96	96	37.32%	27.14201

Table - 46 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for entire next day. Day of week, time of day, temperature from SUS dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	1pm	1344	16	32.83%	18.9009
1000	1pm	2688	16	33.71%	19.81978
1000	1pm	672	16	28.65%	15.60553
1000	1pm	96	16	22.00%	9.760569
5000	1pm	1344	16	29.36%	18.25767
5000	1pm	2688	16	29.91%	17.02152
5000	1pm	672	16	28.39%	14.80568
5000	1pm	96	16	23.20%	9.748342
10000	1pm	1344	16	30.83%	16.48602
10000	1pm	2688	16	31.65%	17.43574
10000	1pm	672	16	27.67%	15.44598
10000	1pm	96	16	22.83%	8.71176
50000	1pm	1344	16	29.69%	18.3909
50000	1pm	2688	16	30.37%	17.41615
50000	1pm	672	16	27.69%	14.97543

50000	1pm	96	16	23.71%	9.491592

Table - 47 Prediction using WEKA regression tree based model. Data collected till 1pm. Predictions are for 1-5pm same day. Temperature from underground dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	4pm	1344	16	26.68%	19.67252
1000	4pm	2688	16	30.07%	20.70555
1000	4pm	672	16	25.91%	18.87846
1000	4pm	96	16	16.90%	14.03689
5000	4pm	1344	16	26.80%	19.25008
5000	4pm	2688	16	30.13%	18.10708
5000	4pm	672	16	23.39%	16.84196
5000	4pm	96	16	15.58%	12.51461

10000	4pm	1344	16	26.13%	18.79449
10000	4pm	2688	16	30.03%	19.66566
10000	4pm	672	16	24.71%	16.87258
10000	4pm	96	16	16.37%	12.54174
50000	4pm	1344	16	26.64%	19.51384
50000	4pm	2688	16	30.79%	20.14442
50000	4pm	672	16	24.89%	17.7213
50000	4pm	96	16	15.78%	13.73877

Table - 48 Prediction using WEKA regression tree based model. Data collected till 4pm. Predictions are for 1-5 pm next day. Temperature from underground dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	16	28.23%	18.99779
1000	midnight	2688	16	28.42%	18.04296
1000	midnight	672	16	25.68%	15.39447
1000	midnight	96	16	20.05%	10.73448
5000	midnight	1344	16	25.14%	19.91568
5000	midnight	2688	16	25.15%	17.27223
5000	midnight	672	16	21.33%	14.91411
5000	midnight	96	16	16.31%	11.12028
10000	midnight	1344	16	25.92%	18.9033
10000	midnight	2688	16	24.81%	17.12128
10000	midnight	672	16	20.84%	15.21726
10000	midnight	96	16	17.47%	11.60839
50000	midnight	1344	16	27.47%	20.91171
50000	midnight	2688	16	23.82%	16.14026
50000	midnight	672	16	22.29%	14.60937
50000	midnight	96	16	17.94%	10.13024

Table - 49 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for 1-5 pm next day. Temperature from underground dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	96	45.22%	38.83429
1000	midnight	2688	96	42.70%	34.44017
1000	midnight	672	96	43.37%	36.42961
1000	midnight	96	96	40.45%	31.42906
5000	midnight	1344	96	43.59%	36.38818
5000	midnight	2688	96	38.78%	29.25594
5000	midnight	672	96	41.11%	31.59977
5000	midnight	96	96	40.54%	31.17875
10000	midnight	1344	96	41.15%	34.59026
10000	midnight	2688	96	38.85%	30.61253
10000	midnight	672	96	39.35%	31.62415
10000	midnight	96	96	38.58%	29.09193
50000	midnight	1344	96	43.43%	38.16632
50000	midnight	2688	96	38.85%	31.11156
50000	midnight	672	96	40.95%	32.49092
50000	midnight	96	96	39.75%	29.80772

Table - 50 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for entire next day. Temperature from underground dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	1pm	1344	16	25.39%	14.5464
1000	1pm	2688	16	26.73%	17.20361
1000	1pm	672	16	24.41%	12.29791
1000	1pm	96	16	21.45%	8.247365
5000	1pm	1344	16	24.55%	11.77962
5000	1pm	2688	16	27.42%	18.24716
5000	1pm	672	16	23.97%	11.16037
5000	1pm	96	16	21.40%	8.426954
10000	1pm	1344	16	24.09%	11.8322
10000	1pm	2688	16	26.41%	17.93782
10000	1pm	672	16	23.61%	11.13003
10000	1pm	96	16	21.40%	8.364933
50000	1pm	1344	16	24.54%	11.97015
50000	1pm	2688	16	26.89%	17.76726
50000	1pm	672	16	23.57%	11.48619
50000	1pm	96	16	21.62%	8.275881

Table - 51 Prediction using WEKA regression tree based model. Data collected till 1pm. Predictions are for 1-5pm same day. Temperature from SUS dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	4pm	1344	16	18.81%	17.00804
1000	4pm	2688	16	23.61%	20.75104
1000	4pm	672	16	18.81%	18.27607
1000	4pm	96	16	14.50%	10.88171
5000	4pm	1344	16	19.15%	18.33434
5000	4pm	2688	16	24.46%	20.51301
5000	4pm	672	16	18.60%	16.20848
5000	4pm	96	16	14.80%	11.30631
10000	4pm	1344	16	18.18%	16.0517
10000	4pm	2688	16	23.93%	19.92828
10000	4pm	672	16	17.59%	15.29106
10000	4pm	96	16	14.84%	11.3496
50000	4pm	1344	16	18.63%	16.50766
50000	4pm	2688	16	23.92%	20.22384
50000	4pm	672	16	18.19%	15.85521
50000	4pm	96	16	14.82%	11.31073

Table - 52 Prediction using WEKA regression tree based model. Data collected till 4pm. Predictions are for 1-5pm next day. Temperature from SUS dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	16	20.71%	17.56296
1000	midnight	2688	16	23.49%	21.33611
1000	midnight	672	16	20.80%	16.44663
1000	midnight	96	16	19.42%	11.07001
5000	midnight	1344	16	19.59%	16.73139
5000	midnight	2688	16	23.56%	21.79146
5000	midnight	672	16	20.64%	15.26842
5000	midnight	96	16	15.69%	10.18952
10000	midnight	1344	16	20.04%	17.22724
10000	midnight	2688	16	23.38%	21.55287
10000	midnight	672	16	20.90%	15.53441
10000	midnight	96	16	15.39%	10.19724
50000	midnight	1344	16	20.69%	17.50183
50000	midnight	2688	16	24.99%	22.89306
50000	midnight	672	16	20.64%	15.60513
50000	midnight	96	16	16.15%	10.33337

Table - 53 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for 1-5pm next day. Temperature from SUS dataset and consumption were used as the features.

Dataset	Historical Data End Time	Historical Data Length	prediction horizon	Error	STD
1000	midnight	1344	96	59.16%	51.96878
1000	midnight	2688	96	67.14%	58.51342
1000	midnight	672	96	56.57%	49.3773
1000	midnight	96	96	36.81%	27.62403
5000	midnight	1344	96	55.08%	47.11047
5000	midnight	2688	96	62.39%	53.09484
5000	midnight	672	96	52.84%	44.83316
5000	midnight	96	96	37.94%	28.30246
10000	midnight	1344	96	55.02%	47.16999
10000	midnight	2688	96	61.65%	52.68445
10000	midnight	672	96	53.53%	45.27678
10000	midnight	96	96	37.76%	28.69089
50000	midnight	1344	96	56.57%	48.66749
50000	midnight	2688	96	63.80%	54.01788
50000	midnight	672	96	53.41%	45.47114
50000	midnight	96	96	37.13%	27.13978

Table - 54 Prediction using WEKA regression tree based model. Data collected till midnight. Predictions are for entire next day. Temperature from SUS dataset and consumption were used as the features.

5. ***Processing Time***

NYISO, CAISO, CASCE and ARIMA 414 are the fastest models as shown in Table 55 below.

Model	**Time**
ARIMA 414 – 1 day	4 min
ARIMA 414 – 7 days	8 min
ARIMA 414 – 14 days	13 min
ARIMA 414 – 28 days	23 min
ARIMA 814 – 1 day	7 min
ARIMA 814 – 7 days	19 min
ARIMA 814 – 14 days	35 min
ARIMA 814 – 28 days	75 min
ARIMA 818 – 1 day	20 min
ARIMA 818 – 7 days	35 min
ARIMA 818 – 14 days	53 min
ARIMA 818 – 28 days	113 min
NYISO	< 1 min
CAISO	< 1 min
CASCE	< 1min
WEKA – 1 day	6 min
WEKA – 7 days	14 min
WEKA – 14 days	27 min
WEKA – 28 days	64 min

Table – 55 Processing time of various models.

6. *Customer Segmentation – Clustering*

6.1 *Incremental Clustering*

Time series forecasting models such as ARIMA can be trained on historical power consumption data to predict the near future based on recent data available from the real-time smart meters. However, two domain challenges emerge when applying such predictive analytics to a large utility service area such as the Los Angeles Power Grid that has over a million consumers: (i) training a prediction model per-customer is computationally costly, and (ii) the variability in the energy usage per consumer causes the prediction models to have high errors. Aggregating data from multiple customers into a single "virtual consumer" helps address both these issues. Besides reducing the number of (virtual) customers to train and prediction for, this can also reduce the temporal variability of the virtual customer, thereby increasing the prediction accuracy. A key goal of this aggregation is to reduce the prediction error of the virtual customer represented by aggregating each cluster of customers. Hence, the novel distance metric used for clustering is, effectively, the degree to which prediction error is reduced by that aggregation, i.e., if adding a customer to a cluster reduces the prediction error, the distance is smaller. This innovative distance measure, unlike Euclidian distances, is valuable when clustering time series data not based on similarity in patterns – which is a very high-dimension problem – but based on their cumulative ability to reduce the prediction error for the cluster. Tradition techniques such as k-means clustering are not directly usable here since there is no distance metric to find the centroid (or medoid) customer for subsequent iterations. So we turn to incremental clustering that offers an approximate but scalable approach. In this paper, we propose the use of an incremental clustering technique to group customers together into virtual customers, with the goal of minimizing the cumulative consumption prediction error. This is distinct from traditional time series clustering that intend to find similarity between data points. Our distance metric selects the affinity of a customer (i.e. time series) to a cluster based on their ability to reduce the cumulative prediction error of the cluster. This approach has polynomial time complexity that scales for large utility service areas.

The goal for our clustering is to group customers whose cumulative energy consumption behaves in a more predictable way and minimizes the ARIMA prediction error for the cluster as a whole. A non-goal, compared to other clustering techniques, is for customers to have "similar" consumption patterns based on distance measures. In fact, customers who have complementary consumption time series patterns may help smoothen the cumulative consumption time series for a cluster. In this process of clustering, we lose information of the predicted consumption for individual customers, which can coarsen the granularity of, say, messaging customers who are good targets for reducing energy demand. Rather than message individual customers, the messages will have to be broadcast to all customers in the cluster. So a secondary goal of our clustering is to reduce the number of customers per cluster. This, paradoxically, means that for a given number of customers, having more clusters is better (without increasing the error per cluster) as it will provide greater decision making power to target fine-grained customers for energy curtailment. This can be achieved by clustering the customers through supervised or unsupervised learning. These clustering techniques have two components: the clustering algorithm and

a similarity measure. In order to computationally scale the problem, we propose to use an incremental clustering algorithm. Each customer's time series data is scanned once and it's suitability with each cluster determined using an affinity score.

6.2 ***Proposed Clustering Algorithm***

The proposed methodology for usage based segmentation consists of the following stages that are performed daily. The assumption is that this operation is performed at midnight of day d for the task of predicting consumption between 1-5pm on day d:

Perform a simple normalization by decomposing the daily electricity consumption time series (i.e., 96 values at a 15-minute granularity per meter). Specifically, given a daily consumption profile *l(t)*, we decompose it as *l(t) = as(t)*, where $a = \sum_{t=1}^{96} l(t)$, and $s(t) = \frac{l(t)}{a}$. a represents the daily total consumption and s(t) is the normalized time-series.

The second stage clusters the normalized time series across the population. Specifically, every time-series $s_n^d(t)$ for day *d* and meter *n* in the dataset is mapped to the closest center C_i^d that minimizes the squared error$E(s, C_i) = \sum_{t=1}^{96}(C_i(t) - s(t))^2$. Finding representative centers that minimize the sum of the mean squared errors over all time-series for day *d* is a standard clustering problem. We solved this problem using the K-means algorithm, a popular statistical clustering approach. Algorithm 1 summarizes the main steps of the proposed approach.The classic K-means algorithm needs the number of clusters, *K*, to be known a-priory. In order to decide a proper value for K, considering the large number of potential candidate for representative time-series "shapes", we used the Dunn's index. Similar to other indices, the aim is to identify sets of clusters that are compact, with a small variance between members of the cluster, and well separated, where the means of different clusters are sufficiently far apart, as compared to the within cluster variance. The reason for choosing this evaluation metric is that there is no ground truth about the number of clusters. Specifically, unlike other metrics, Dunn's index is an internal evaluation scheme, where the result is based on the clustered data itself.

Algorithm 1. Proposed Clustering Algorithm based on K-means
Require: Daily time-series $s_n^d(t)$ for all meters n ϵ N, min and max number of clusters *for k ϵ [min number of clusters, max number of clusters]* *run K-means* *calculate Dunn's Index* *if the Dunn's Index for this configuration is minimum* *return the clustering results and K = k*

end

end

The third step is to train a forecasting model per cluster to improve the prediction error as compared to a model that is trained on the complete population. For this task, we took a data driven approach consisting of obtaining a functional model that relates the value of the response variable $s_n^d(t)$ with the values of predictor variables $s_n^d(t-2), s_n^d(t-1)$. Other features can be explored. Specifically, we use a regression tree as a predictive model which maps predictor variables $s_n^d(t-2), s_n^d(t-1)$ to $s_n^d(t)$. A regression tree is "learned" by splitting the source dataset into subsets based on an attribute value test. This process is repeated on each derived subset in a recursive manner called recursive partitioning. The recursion is completed when the subset at a node has all the same value of the target variable, or when splitting no longer adds value to the predictions. Finally, a simple regression model is fit to the small data that belong under each node. We perform this process independently for each cluster; a regression tree is thus learned for each cluster.

The last step is to perform predictions for each time-series $s_n^d(t)$ for day *d*. Recall that the objective of learning a regression tree is to learn a model for predicting the response $s_n^d(t)$ with the values of predictor variables $s_n^d(t-2), s_n^d(t-1)$. Given a forecast or availability of observed values for $s_n^d(t-2), s_n^d(t-1)$ we can predict the response $s_n^d(t)$.

6.3 ***Results***

ARIMA	Number of Clusters	Training Data Size	End Time	Error	Std
414	50	96	1pm	10.49%	8.33%
414	25	96	1pm	8.64%	7.78%
414	10	96	1pm	8.25%	7.30%
414	5	96	1pm	7.56%	6.89%
414	2	96	1pm	7.70%	6.82%
414	1	96	1pm	7.66%	6.37%
814	50	96	1pm	9.64%	7.85%
814	25	96	1pm	8.50%	7.15%
814	10	96	1pm	8.51%	7.56%
814	5	96	1pm	7.87%	6.96%
814	2	96	1pm	7.55%	6.69%
814	1	96	1pm	7.63%	6.66%

Table - 56 Results of clustering with ARIMA for data until 1pm

ARIMA	Horizon	Error	Std
414	4pm	19.80%	19.63%
414	midnight-DR	20.18%	17.30%
414	midnight-24hrs	24.72%	15.76%
814	4pm	20.54%	19.90%
814	midnight-DR	20.15%	15.44%
814	midnight-24hrs	26.02%	17.41%

Table - 57 Results of clustering with ARIMA for data until 4pm for DR, midnight for DR and midnight for 24h horizon prediction

Cluster #	scenario	past data	prediction horizon	Prediction Error	Error std
1	1pm	1344	16	16.64%	14.510161
1	1pm	2688	16	16.85%	14.645282
1	1pm	672	16	17.25%	14.891452
1	1pm	96	16	23.26%	10.60615
1	4pm	1344	16	20.62%	16.842081
1	4pm	2688	16	21.39%	18.501717
1	4pm	672	16	21.48%	19.230018
1	4pm	96	16	17.43%	14.289692
1	midnight	1344	96	16.83%	79.022447
1	midnight	2688	96	16.15%	76.988471
Cluster #	scenario	past data	prediction horizon	Prediction Error	Error std
1	midnight	672	96	20.40%	81.499937
1	midnight	96	96	69.96%	117.505018
1	midnight	1344	16	17.23%	17.140126
1	midnight	2688	16	17.21%	18.500757
1	midnight	672	16	18.51%	18.197374
1	midnight	96	16	46.74%	63.887223
2	1pm	1344	16	17.01%	13.749807
2	1pm	2688	16	16.70%	13.141947

2	1pm	672	16	17.56%	12.618671
2	1pm	96	16	23.02%	11.138985
2	4pm	1344	16	20.75%	18.175722
2	4pm	2688	16	21.50%	18.577995
2	4pm	672	16	21.48%	19.553419
2	4pm	96	16	18.37%	14.613596
2	midnight	1344	96	17.22%	25.329217
2	midnight	2688	96	16.30%	23.409898
2	midnight	672	96	20.34%	30.42587
2	midnight	96	96	46.89%	64.505948
2	midnight	1344	16	16.82%	13.845261
2	midnight	2688	16	16.68%	13.782277
2	midnight	672	16	17.01%	14.165403
2	midnight	96	16	34.16%	31.724571
3	1pm	1344	16	17.49%	13.67266
3	1pm	2688	16	17.68%	13.674296
3	1pm	672	16	18.49%	14.301455
3	1pm	96	16	24.25%	11.820947
3	4pm	1344	16	20.31%	19.080475
3	4pm	2688	16	22.13%	19.632446
3	4pm	672	16	19.93%	17.360806
3	4pm	96	16	17.63%	14.214693
3	midnight	1344	96	17.09%	18.955572

3	midnight	2688	96	16.96%	19.687663
3	midnight	672	96	19.78%	23.63116
3	midnight	96	96	55.15%	75.794371
3	midnight	1344	16	18.35%	15.70636
3	midnight	2688	16	17.79%	14.820958
3	midnight	672	16	20.06%	16.624984
Cluster #	scenario	past data	prediction horizon	Prediction Error	Error std
3	midnight	96	16	40.66%	46.320164
4	1pm	1344	16	22.71%	93.406396
4	1pm	2688	16	173.32%	2548.702984
4	1pm	672	16	23.40%	93.405265
4	1pm	96	16	29.76%	92.652205
4	4pm	1344	16	22.70%	23.259704
4	4pm	2688	16	28.53%	128.913913
4	4pm	672	16	22.50%	23.015168
4	4pm	96	16	18.30%	18.90326
4	midnight	1344	96	1706.52%	30761.80523
4	midnight	2688	96	1865.87%	33463.40381
4	midnight	672	96	3677.57%	66746.17098
4	midnight	96	96	3669.86%	66004.16429
4	midnight	1344	16	2345.14%	38826.11772
4	midnight	2688	16	2549.68%	42236.31719

4	midnight	672	16	5066.57%	84245.26995
4	midnight	96	16	5029.75%	83308.1246
5	1pm	1344	16	173.84%	1266.306891
5	1pm	2688	16	187.16%	1349.426221
5	1pm	672	16	121.85%	853.685483
5	1pm	96	16	58.66%	403.958018
5	4pm	1344	16	372.64%	2035.204243
5	4pm	2688	16	353.74%	1773.824164
5	4pm	672	16	284.80%	1596.460072
5	4pm	96	16	216.11%	1604.160221
5	midnight	1344	96	1210.55%	18662.16205
5	midnight	2688	96	207.20%	1745.003908
5	midnight	672	96	1964.43%	21567.63657
5	midnight	96	96	6598.13%	63262.01791
5	midnight	1344	16	481.65%	3836.643938
5	midnight	2688	16	177.68%	1266.833195
5	midnight	672	16	696.27%	3937.318568
5	midnight	96	16	1931.33%	7679.640167

Table - 58 Results of clustering with WEKA. Given a daily clustering configuration, predictions are made for each cluster individually. A model is trained per cluster on the summation of consumption values in each cluster and prediction is made for the summation of the values inside each cluster.

7. *Curtailed Consumption*

7.1 *Curtailment Prediction*

Using the past curtailment data, predict the curtailment for today's DR. A pre-defined baseline is required to calculate the curtailment against.

4pm: The baseline here is predicted by using ARIMA 8,1,4 with 1 day of training data which ends at 4pm of the previous day.

midnight: The baseline here is predicted by using ARIMA 814 with 1 day of training data which ends at midnight of the previous day.

ARIMA	Horizon	Error	Std
814	4pm	19.30%	26.70
814	midnight	43.90%	9.44

Table – 59 Curtailment prediction results

7.2 *Curtailed-Consumption based Prediction*

Using the past consumption data during DR event, predict today's reduced consumption. Use a pre-defined baseline to calculate the curtailment by subtracting the predicted reduced consumption.

4pm: The baseline here is predicted by using ARIMA 814 with 1 day of training data which ends at 4pm of the previous day.

1pm: the baseline here is the actual consumption data at 1pm.

midnight: The baseline here is predicted by using ARIMA 814 with 1 day of training data which ends at midnight of the previous day.

ARIMA	Horizon	Error	Std
814	4pm	26.79%	48.00
814	1pm	17.64 %	13.91
814	midnight	27.83%	79.43

Table – 59 Curtailed-Consumption based prediction

Note that in this approach, the consumption data of morning 9-12 of the DR day is used for scaling the reduced consumption to account for environmental conditions on DR day. The consumption data are predicted using the ARIMA model as mentioned above.

8. *Conclusion*

8.1 *Best Model with regards to Error*

Given the performance of all methods; namely, ARIMA, CAISO, NYISO, CASCE, and WEKA, we believe ARIMA outperforms all other methods. We make this conclusion based on the small error and standard deviation that ARIMA has compared to other methods. The small standard deviation makes the predictions more reliable. Note that NYISO and CASCE offer better error rate for some cases, however, the larger standard deviation causes them to be considered as a secondary choice.

The one exception is the scenario where the predictions are made for entire next day. In this scenario, NYISO performs better and should be used instead.

8.2 *Best Model with regards to Processing Time*

NYISO, CAISO, CASCE all have similar running times which are the lowest among the models evaluated in this study.

Appendix AT Final Technical Report Smart Grid Regional Demonstration Project (SGRDP) Demand Response DR-CB3 Scenario #2

Final Technical Report

Smart Grid Regional Demonstration Project (SGRDP)

Demand Response DR-CB3 Scenario #2

Enabling and demonstrating residential customers with HAN participating in Automated Demand Response

University of California Los Angeles (UCLA)

Los Angeles Department of Power and Water (LADWP)

Aug 2016

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ABSTRACT

Automated demand response has the potential to allow electric utilities to independently monitor and control customer premise loads to reduce peak electricity demand. Despite its convenience, widespread implementation of this energy management system depends on several uncertain factors:

- Customer acceptance of utility-automated demand response programs
- Reliable transmission of demand response signals from their source to desired loads (such as heating, ventilation, and air conditioning systems, electrical appliances, plug loads, lighting systems, and electric vehicles) through adequately robust communications infrastructure
- Automatic and intelligent reduction of a given amount of electrical load within a given time interval in a utility provider's service area

In this report, the research team describes the design, simulation, and results of an automated demand response test bed that provides a platform to investigate intelligent electrical load reduction. The test bed includes a variable refrigerant flow, air conditions, washer dryer and other appliances that will typically be part of aggregate demand response resources in small commercial and residential demand response markets. Home Area Networks (HANs) will connect appliances, on-site renewables, and storage devices in homes to the grid for access to real-time energy usage and pricing information, and providing the ability to react to demand response events from LADWP.

HAN has the potential to become a significant resource for demand side management impacting home owners, utilities and smart grid vendors. HAN allows remote monitoring and control of home appliances and gadgets. In this project various HAN technologies have been developed that enable intelligent control of electrical loads inside customers' premises in response to utility signals. The control and monitoring system can manage individual electrical load or aggregate loads. Control and data flow is secured by industry approved encryption schemes, and automatically provides protocol translations, electricity usage records, and electrical load states. HAN has been successfully integrated with Demand Response Management System comprising of Demand response Automation Server (DRAS), Demand Response Data Repository for scheduling and managing demand response programs based on OpenADR specification.

An open, standards-based, and flexible architecture for HANs is important to ensure longer life as the technology evolves. This demonstration involves protocols and prototypes for communications, and sense-and-control and information-based systems for HAN using UCLA WINSmartGrid technology.

The design emphasis of the technology was to develop an architecture that would facilitate automatic resource selection for load curtailment or on-site supply to support energy shed, shape, shift or substitute modes for demand adjustment. The test bed achieved automated load curtailment without participant intervention, minimizing the customer inconvenience factor that has substantially lowered the participation rate in utility demand response programs.

1. Project Description

1.1. Executive Summary

Demand response (DR) is a method of maintaining electric grid stability in which end-use customers voluntarily modify the amount or timing of their energy consumption in response to energy pricing or grid reliability signals. This method began as a strategy to avoid system emergencies in the electric grid during periods of peak electricity demand. With technological advances and innovations, DR has evolved to provide a variety of additional services that promote energy efficiency, system reliability, reduce energy cost, reduce greenhouse gases, and integrate renewable generation; however, these rapid developments have yet to reach electric utilities' desired range of customers, particularly the residential service base, due to:

- The lack of smart end-to-end solutions that keep customers engaged with discernable stream of benefits.
- The lack of DR friendly, do-it-yourself, and inexpensive control technology for home owners.
- The dearth of intuitive DR programs and strategies.
- Above all, the scarcity of analytical tools that measure and validate DR participation and load curtailment reliably.

In this project, the research team explored solutions for some of the aforementioned issues that are restricting access to new developments in DR by proposing:

- An automated demand response (ADR) network architecture.
- Electric load control technology with integrated open automated demand response (OpenADR) clients. OpenADR is a communication protocol that allows electrical utilities to send DR signals to their customers.
- Design of demand response resource specific DR strategies.

The scope of the project includes the design, development and testing of an HAN and ADR test bed that incorporates these strategies on the University of California, Los Angeles (UCLA) campus.

1.1. Introduction

Smart grid is an intelligent electrical grid that will distribute electricity from distributed generating resources to consumers under the supervision of two-way digital communications that will monitor, regulate, and control generation, distribution, storage, and consumption. It is anticipated that this automation will boost distributed control, minimize energy losses, enhance reliability, and promote effectual consumption across the electrical ecosystem economically (Mitchell et al. 2014; Smith 2010).

This transformation from traditional electric grid demands innovations on multiple fronts on a large scale, warranting experimental research, investigation, and validation before technologies, architectures, and operations can be assimilated by the industry. Smart grid research test-beds allow testing of advanced technologies, business processes, market models, innovative strategies and programs required to investigate and evaluate the new enabling components of smart grid such as renewable energy

generation, electric vehicle infrastructure, microgrids, communication networks, control strategies, and customer engagement (Jarred 2014; Epstien et al. 2005).

Demand response (DR) is emerging as an application in the smart grid ecosystem. DR programs essentially depend on reduction in electricity demand during grid stress and primarily rely on load management by modifying power consumption to align power demand and supply. For DR to be successful, a collection of technologies, strategies, and software components in addition to customers' commitment is crucial. Since there are a myriad of potential solutions for achieving this goal, a preliminary evaluation of such solutions would assist in selecting a best- of-breed solution. A test-bed consisting of these technologies, software components and means to design and execute DR strategies would be invaluable as there are challenges to successful integration of demand response solutions. Challenges are systems architecture and integration, reliable control technology and strategies, consumer technology, fragile cyber security, fostering customer interest and engagement, measurement and validation, and policy lag and confusion (O'Connell et al. 2014; Spam, Jin, and Earle 2013, Thayer et al. 2015, Research into Action, 2015).

This research project attempts to develop solutions that may mitigate some of the above challenges and pave way towards durable solutions. The focus was on developing a system architecture that supports automatic DR for a large UC campus with a captive distribution system that produces 85 percent of the campus power by a cogeneration plant, managing the campus distribution and auxiliary systems, deploying DR control intelligence, and using battery storage as a demand response.

In addition, a low-cost DR simulator was developed that may be used to estimate the curtailable load available for a particular DR event based on the customer preferences to provide a curtailable baseline, evaluate the impact of aggregation of types of curtailable loads during a DR event and use it as a DR learning tool for dispatchers and facility managers.

The following sections describe the development of the above solutions and planned experiments for monitoring and controlling of DR resources and different strategies using them.

1.2. ***Motivation***

A research focus of the project was to investigate the potential of enabling automated control of residential electric loads by adding onboard capability to directly process OpenADR signals and manage control cycles to minimize electricity use within the constraints of customer specified end-use preferences. The investigation involved evaluating controller design, communications reliability, and robustness, system health and measuring DR performance.

1.3. ***Project Purpose***

The purpose of this project was to explore the feasibility of an OpenADR-friendly end-to-end solution that could:

- Host OpenADR software on the (ReWINS) server technology developed at the Smart Grid Energy Research Center (SMERC) at UCLA.
- Have OpenADR accommodate customer preferences and execute DR strategies in response to DR events automatically with little-to-no intervention from the customer.
- Support intelligent DR programs and strategies that work with AutoDR.

1.4. Project Process and Results

A test bed consisting of Home Area Network controlled appliances in a graduate housing complex with an OpenADR-friendly control system, available at existing UCLA DR test bed using smart appliances, smart lighting, and electric vehicle (EV) charging infrastructure.

To perform the research, the research team divided the project into the following:

- AutoDR Architecture: A services-oriented architecture was selected suitable for the smart controls and use of common hypertext transfer protocol (HTTP) methods that simplify implementation and minimize network traffic. The architecture allowed efficient exchange of planned DR events and signals and managed electrical loads.
- DR modeler and simulator: A DR simulator supported by a data model called Electric Service Model that represents residential service, electric loads, and user priorities and preferences successfully selected the target curtailment that complied with the customer's preferences.

1.5. Project Benefits

In spite of the small scale of the project for an AutoDR solution, the successful demonstration of an OpenADR client design hosted on control platforms, (2) DR resource specific curtailment strategies, and (3) the execution of DR strategies guided by associated user preferences, has provided a system to alleviate some of the aforementioned challenges inherent in implementing residential DR programs.

The DR programs and strategies exhibited in this project can be part of the DR portfolio on the UCLA campus and are expected to guide campus renovation and modernization projects.

SMERC also believes that these technologies and strategies would benefit LADWP by providing means to directly automate discrete end-point loads that are OpenADR conversant and render them capable of participating in demand response programs with minimal human assistance. An automated network of smart loads would also provide detailed grid visibility in real-time to utilities (LADWP) to develop analytics and forecasting systems facilitate dispatching strategies. The proposed framework is also adaptable to all types of customers and can be deployed under aggregated management and control schemes.

1.6. Location and Potential of DR Platform

The test-bed is multi-locational and the demand response resources include smart appliances, smart communicating thermostats in a graduate student apartments and the demand response test rig in UCLA's Smart Grid Energy Research Center (SMERC) lab. The location of the test bed is as shown in the Figure 17.

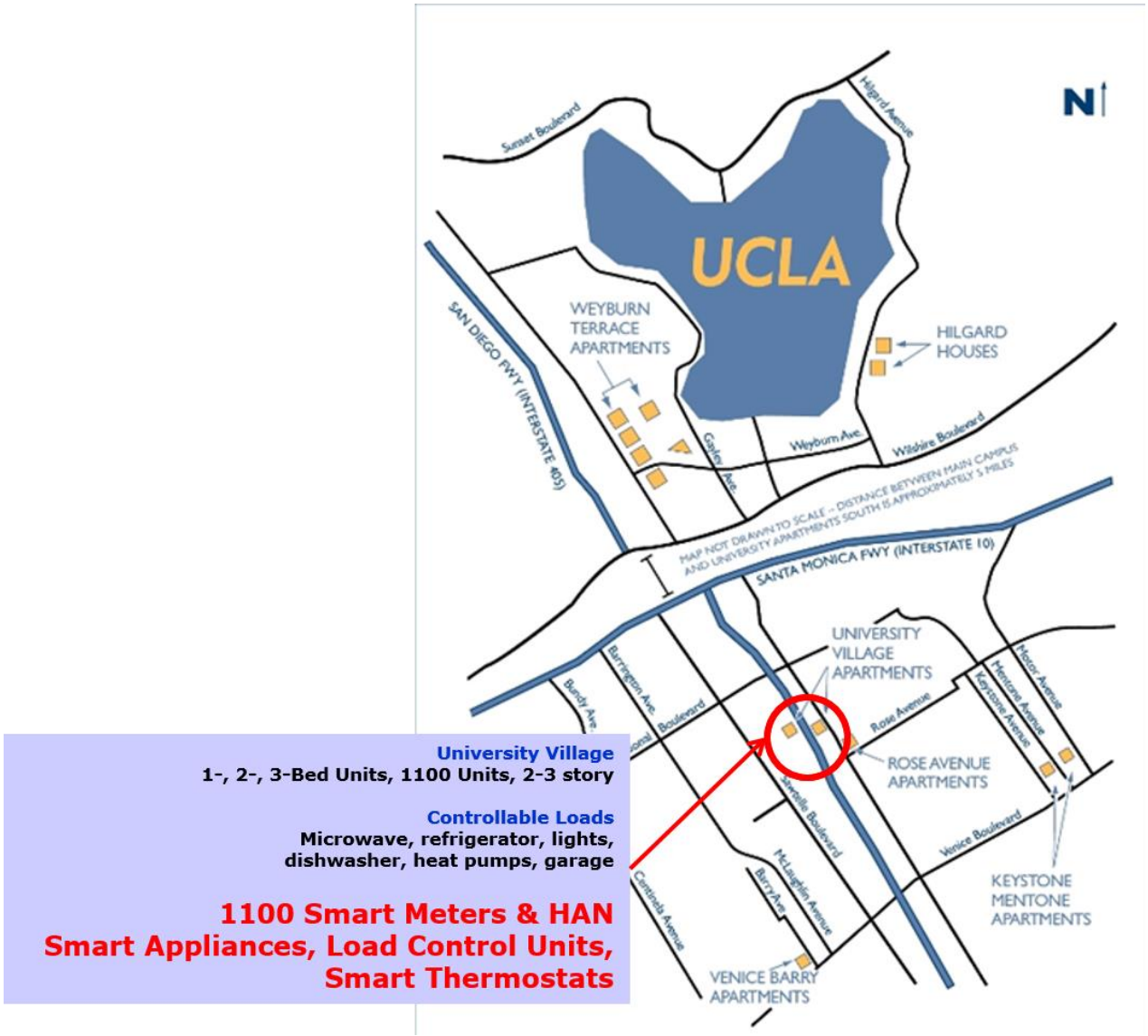


Figure 17. UCLA Demand Response Test Bed

1.7. Automated Demand Response (AutoDR) Facility

The test-bed was designed to support automated DR that enables reduction in electrical loads in response to utility / facility requests without human intervention using a REST architecture based solution that supports secure two-way communication between the smart control clients and the demand response server.

1.8. Automated Demand Response System

The architecture of the OpenADR specification compliant Demand Response Automation Server meet the interoperability requirements of an architecture that is integrated and hosted within the UCLA facilities IT infrastructure. The distributed client-server architecture supports continuous, two-way, secure messaging between facilities and the participating customers.

Service-orientation is based on the Representational State Transfer (REST) paradigm developed by UCLA. This exploits the benefits provided by REST Web services that are lightweight, maintainable, and scalable. In the context of the constrained smart demand-side controls that are essential for automating DR, the REST Web Services provides many advantages, such as reduced network traffic, minimum coupling between client and server components, lightweight requests and responses, and explicit use of HTTP methods (Shelby 2010; Laine 2011).

This architecture is ideal for Web-enabling the smart controls in building automation systems (BAS) or *home area networks* (HAN) as it facilitates networking of clients (smart controls) with a variety of capabilities using the uniform HTTP interface with the Web. The use of HTTP protocol and basic Web axioms in REST simplifies interaction between server and client on smart controls of devices, appliances, and gadgets.

Section 3 describes the experimentation plan for the DR architecture in HAN to support smart controls for a variety of residential smart electrical loads.

1.9. Residential Demand Response Modeling and Simulation

Peak demand reduction potential in residential energy market is very promising and is mostly untapped. Getting a definitive estimate of the controllable load base is challenging due to the granularity, diversity of electrical loads, and diversity in end-use.

In this project a consumer level, low cost simulation tool is proposed to assist in identifying the potential load base. To support this, an *Extensible Markup Language* (XML)-based Electrical Service Model (ESM) was developed. This model is a hierarchic representation of a residential dwelling unit as an electrical demand response resource. The hierarchy consists of the electric service size, circuit and sub-circuit size, appliances, plug-loads, lighting, and so forth. The model forms the base for the DR simulation modules in association with end-use preference settings for individual electrical controllable loads. The simulator may be used to run interruptible / curtailable DR events against individual ESM, aggregate ESMs, and aggregate load types from available ESMs. It is also useful as a learning tool.

Modeling ESMs, simulating a DR event run and results of the proposed curtailment service is presented in detail in section 3.

2. Communications protocol and prototype Home Area Network (HAN) using

WINSmartGrid Technology

2.1. *Methodology*

To demonstrate these use cases and meet the success criteria for this demonstration, the Demand Response team will integrate the historical and real-time AMI and system data for making outage and demand-side load management decisions. Additionally, the LADWP Demand Response team will provide HAN and HEM services to customers to better educate customers about how interactive energy management applications work and will also be a means of providing customers with the ability to set preferences to control how and when their appliances and other equipment use energy. Also, a Home Energy Management program will be available to those interested in a HAN demonstration. This will be a source of data and implementing it for load forecasting and load curtailment.

2.2. *Planned Approach to Evaluation, Investigation and Development of HAN*

In order to successfully demonstrate Demand Response through HAN a number of technology, hardware, software, database, process / business logic and deployment test bed related issues had to be researched and inspected. This study was very important as the solution had to meet a number of essential requirements such as LADWP's IT architecture, security, and customer privacy, need for automated Demand Response and interoperability with other technologies, applications and systems of the project. Following is the summary of key components of the solution that required investigation and development:

a. Data repository had to be designed to store smart meter, appliance and DR participants' data in order to separate the data from LADWP databases on account of non-availability of required schema support, avoid pollution of data of LADWP databases and facilitate a service topology that is isolated from LADWP production IT infrastructure for security purposes.

b. As pertinent Demand Response software / applications were not available within LADWP IT infrastructure, it was necessary to design and develop appropriate software. Service-Oriented Architecture (SOA) based design was selected for the Demand Response software as SOA facilitates enterprise agility by way of supporting agnostic technology stacks, mitigating configuration constraints, providing flexibility to re-combine functions to meet changing requirements, simplifying integration of new functionality with minimum disruption, promoting operational scalability, and bolstering loose coupling with database and system technologies.

c. Custom automated HAN control units had to be designed and developed as control units with native OpenADR support were not available off-the-shelf. Since it was decided to use OpenADR for Demand Response control units were developed on a single board computer (SBC). The embedded system based on WINSmartGrid technology has on-board OpenADR client and capable of executing demand response signals received directly from the server.

d. WiFi (IEEE 802.11 b/g/n) communications and networking was selected over ZigBee, Z-Wave and Insteon technologies. During evaluation it was found that ZigBee, Z-Wave and Insteon had the following shortcomings :

    (a) Interoperability between technologies from different vendors
    (b) Communication range was short and inconsistent compared to WiFi

(c) WiFi was more reliable
(d) Licensing of Z-Wave and ZigBee was costly than WiFi
(e) WiFi provides larger and robust bandwidth which was essential to connect 10-12 control units to the network as would be required in a typical residence

2.3. ***WINSmartGrid Technology***

UCLA developed created WINSmartGrid to extend ReWINS technology to support remote intelligent electrical load controls by implementing the firmware architecture on a commercial off-the-shelf single board computer (SBC). The design has progressed through multiple SBCs like Arduino and Raspberry Pi. SBCs are single circuit boards with integrated processor, memory, input/output pins or slots, communications, and video interfaces that operate at low power, are small sized, cost-effective and provide full-sized computer's functionality. They are capable of running multiple flavors of operating systems selectable as required by the applications and support embedded databases for high-performance data logging needs. This configuration and features of SBCs has proved an ideal control platform for specific WINSmartGrid embedded applications being prototyped.

In the current version of the technology, the Home Area Network (HAN) control is provided through two WINSmartGrid platforms called the Smart Gateway and the Appliance Controller. In addition to the capabilities of ReWINS, WINSmartGrid platform firmware has an embedded OpenADR client. The smart gateway connects to the network and monitors the availability of a DR event. On receiving a valid DR event, the smart gateway manages the preset load management protocol of all the appliance controllers connected to the smart gateway in the HAN setup.

2.3.1. Subsystems/components and their interactions

The home area network (HAN) handles demand-side management and constitutes the smallest residential subsystem in the hierarchical table of a smart grid, interconnecting with a separate subsystem, like LADWP network. The HAN also networks smart appliances with sensors and actuators, in-home displays, smart meters, and home energy management systems. The HAN must respond to the utility company's DR signals and facilitate intelligent control of electrical loads inside the customer's premises based on the customer's preferences. To accomplish these aims, a sophisticated HAN must provide: 1) network communication with the utility company and the consumers' electrical loads; 2) storage of electricity usage records for transmission to the utility; 3) storage of electrical load states for appliance control; 4) protocol translation to support multiple appliances with proprietary interfaces, and 5) consumer preference engine to affect appliance function based on the customer's preferences. These functions are fulfilled using three primary components: communication network, smart in-home gateway, and appliance controllers.

2.3.2. Technologies and systems used in the demonstration

The key technologies used in the demonstration are the communication network, smart gateway and the load/appliance controller.

2.3.2.1. Communication Network

The HAN supports communication among heterogeneous devices and appliances using various network protocols, including Wi-Fi, Ethernet, power-line communication (PLC), Insteon, X10, and ZigBee. In particular, a ZigBee mesh network based on COTS ZigBee nodes interfaces with appliance controllers and the in-home smart gateway.

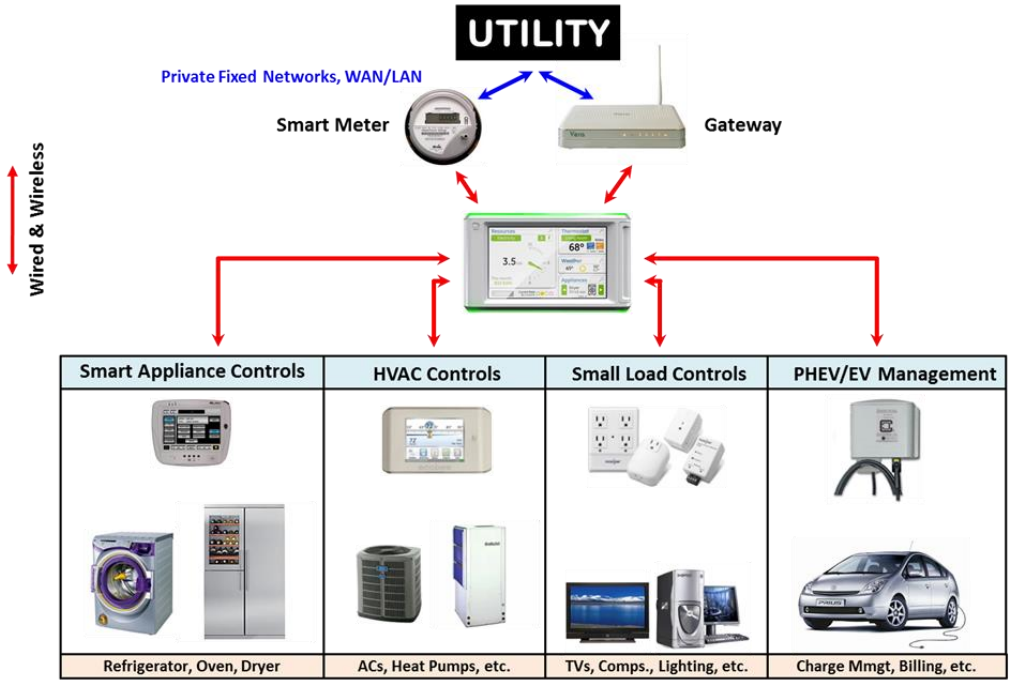


Figure 18. Communication Network

2.3.2.2. Embedded system

An organic embedded system has been developed to support communications, data / protocol translation, control and monitoring of the HAN. The key modules of the embedded system developed for the smart gateway, load / appliance controller and the host are as shown in figures below.

The embedded system developed C runs on Linux platform. The key features of the system are

a. Intelligent control and monitoring – registration of control units with the gateway, auto-restart, auto-reconnect, data logging, data purging, communication over HTTPS transport, authentication and authorization

b. On-board data persistence to log connectivity, energy consumption and demand response event related data. Intelligent self-manageable buffers were implemented

c. Control protocol translation facilitates the conversion of DR event data into control unit operations – switch off/on, dimming, and modify cycle times

d. Client – server communications is based on client-side polling as this model simplifies the network address translation issues of control units that are invariably deployed behind the access point firewalls.

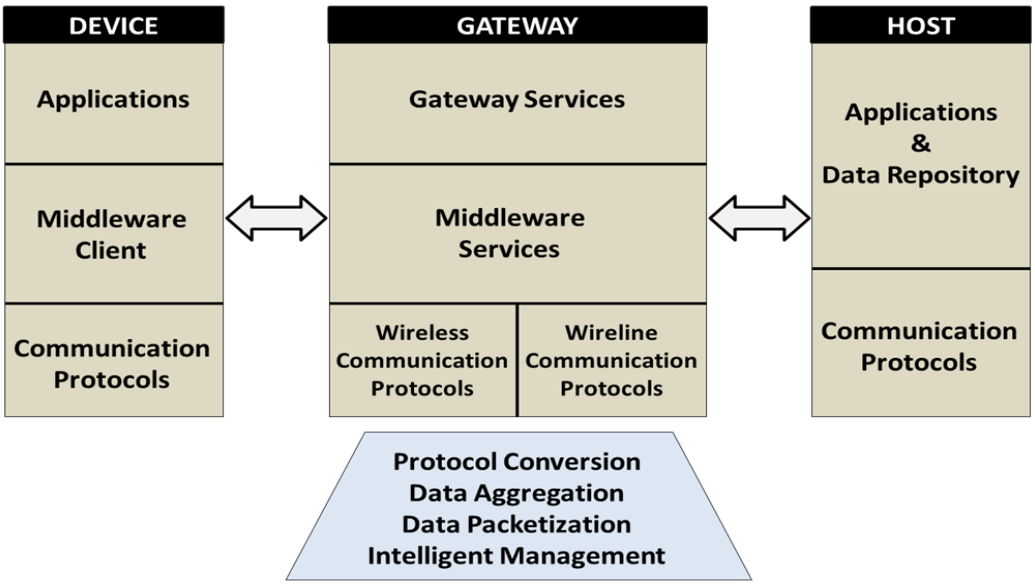


Figure 19. HAN embedded system modules

2.3.2.3. Smart Gateway

The smart gateway is implemented using the SBC with Wi-Fi and a ZigBee dongle. It includes a real-time clock and keeps track of time using network time protocol (NTP) connected to a public NTP server. The gateway connects to the main server using secure shell (SSH), which is left open for secured and encrypted communication; thus allowing a channel for PUSH and PULL interaction methods for data exchange and updates to the firmware.

Smart gateway connects the HAN to external network systems, such as the LADWP's network, and manages all devices within the HAN. The gateway has six primary functions: network communication and appliance management, storage of electricity usage records and electrical load states of appliances, privacy protection of the end users' energy data, DR signal response generation, and consumer preferences management. Figure 20 shows the smart gateways being tested and Figure 21**Error! Reference source not found.** shows a typical preference selection screen.

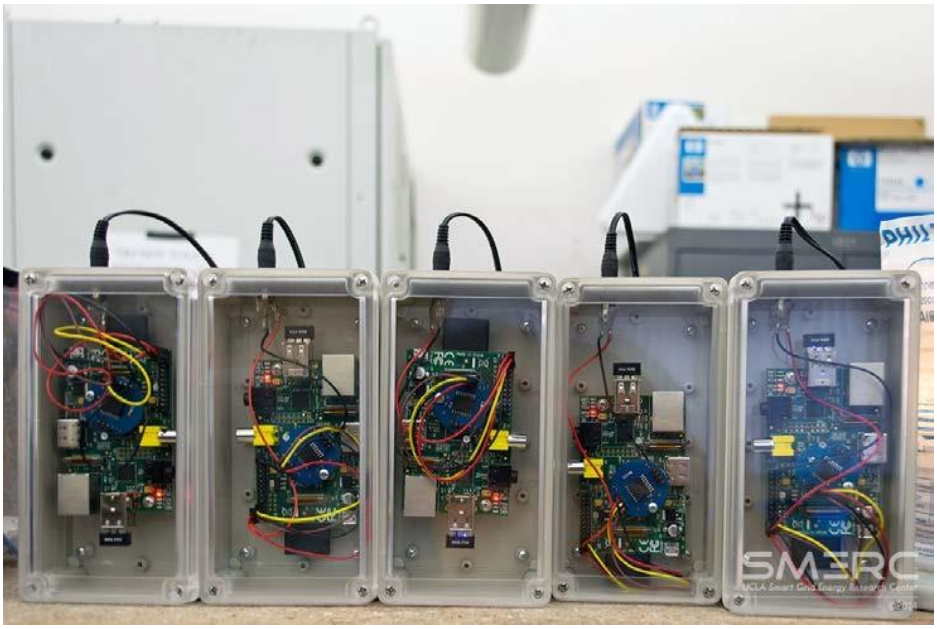


Figure 20. WINSmartGrid Smart Gateway

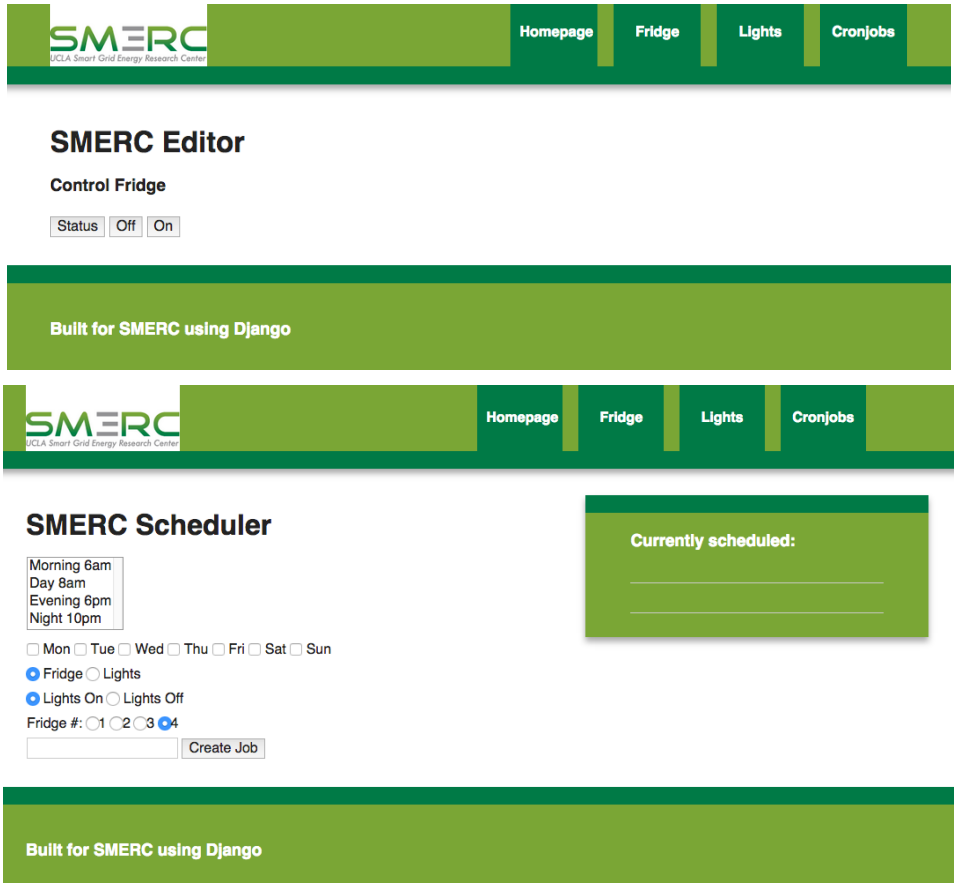


Figure 21. Preference Manager

The gateway maintains two-way communication between the HAN's end devices and external systems, in the utility company or campus facility using onboard Ethernet or Wi-Fi modems.

The gateway also acts as a network endpoint inside the customers' premises establishing network connectivity with network-enabled electrical loads, such as appliances, digital thermostats, load control units such as smart plugs 15 A/30A, electrical outlets, and switches.

The gateway collects electricity usage records and individual electrical load states of appliances within the HAN and stores this data on the main server's database., the gateway also collects electricity usage data from the sub-meter in the controllers in intervals of as low as a second and communicates that information to the utility for monitoring; this data is stored by the gateway and the main server's database. For the electric load states of appliances, the appliance controller of each end-device communicates with the smart gateway to transmit the device's energy status. The data from the smart meter and appliance controllers are used by the gateway to manage energy consumption profiles of registered loads within the HAN. In addition, the gateway protects consumer privacy by limiting the consumer's energy data that the utility company can see.

Whenever the gateway receives a DR event signal, it generates a translated DR signal for each appliance. The translated DR signal stores the following data: timestamp when the signal is generated; duration of the DR event in seconds; and timestamps for when the curtailment event goes into effect and when it ends. These data are stored in the translated demand response signal that the gateway pushes to the end device's appliance controller for fulfillment of the load curtailment based on consumer preferences. Once the curtailment ends, the appliance controller collects the energy status information from the appliance and transmits the post-DR event data to the gateway, which pushes the data to the main server.

Salient features of the smart gateway:

e. Acts as a network endpoint inside the customer premise that maintains two-way communication between the LADWP's Network and HAN.

f. Assists commissioning of HAN and DR account registration with the utility DRMS

g. Manages energy consumption profiles of registered loads that are capable of self-metering

h. Provides network connection through wired Ethernet, WiFi, and/or ZigBee

i. Establishes network connectivity with network enabled electrical loads appliances, digital thermostats, load control units, electrical outlets and switches, etc.

j. Assists customer preferences management for registered electrical loads. Preferences set to particular day, particular time of day, and type of response to utility DR event

k. Manages the entire lifecycle of OpenADR signal. Loads will be shed, shaped, or shifted

l. Manages the acknowledgement channel with DRMS to update the scheduled response to the LADWP's DR event

The smart gateway connects the HAN to external network systems, such as the LADWP's network, and manages all devices within the HAN. The gateway has six primary functions: network communication and appliance management, storage of electricity usage records and electrical load states of appliances,

privacy protection of the end users' energy data, DR signal response generation, and management of consumer preferences. Smart gateway architecture schematic is shown in

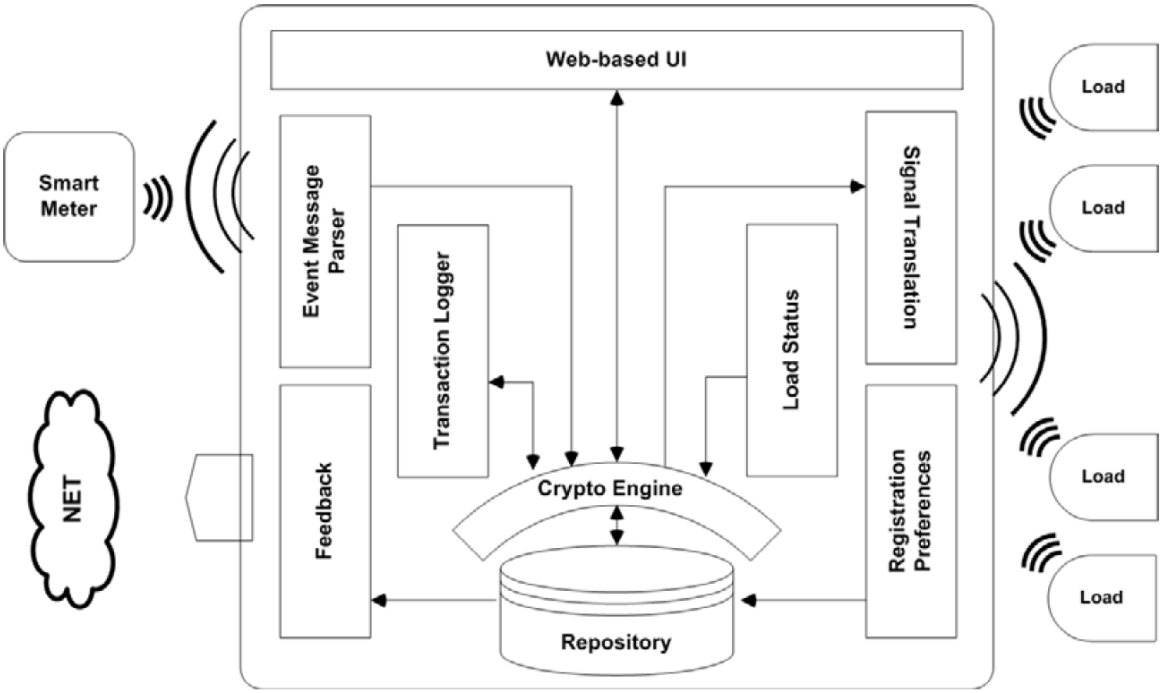


Figure 22. Service Gateway Architecture

The gateway maintains two-way communication between the HAN's end devices and external systems, such as the utility company, by enabling continuous bi-directional communication via a smart meter. The gateway also acts as a network endpoint inside the customers' premises establishing network connectivity with network-enabled electrical loads, such as appliances, digital thermostats, load control units, electrical outlets, and switches.

The gateway collects electricity usage records and individual electrical load states of appliances within the HAN and stores this data on the main server's database. To collect electricity usage records, the gateway connects to the smart meter that records consumption of electricity in intervals of an hour or less and communicates that information to the utility for monitoring; this data is stored by the gateway and the main server's database. For the electric load states of appliances, the appliance controller of each end-device communicates with the smart gateway to transmit the device's energy status. The data from the smart meter and appliance controllers are used by the gateway to manage energy consumption profiles of registered loads within the HAN. In addition, the gateway protects consumer privacy, by limiting the energy data of the consumer that the utility company can see.

Whenever the in-home gateway receives a DR event signal, it generates a translated demand response signal for each appliance. The translated demand response signal stores the following data: timestamp

when the signal is generated; duration of the DR event in seconds; and timestamps for when the curtailment event goes into effect and when it ends.

These data are stored in the translated demand response signal that the in-home gateway pushes to the end device's appliance controller for fulfillment of the load curtailment based on consumer preferences. Once the curtailment ends, the appliance controller collects the energy status information from the appliance and transmits the post-DR event data to the in-home gateway, which pushes the data to the main server.

In order to respect the customer's wishes with regard to energy loads, the in-home gateway implements a consumer preference engine that is used to curtail an appliance's load while taking into account the owner's choices. For instance, when the gateway receives a DR event, the gateway generates a translated DR signal that it pushes to select appliances that are determined after consulting the preferences set by the user. The user can set the preferences via an HTML page that is hosted on either the in-home gateway or the main server. If the preferences are set on the main server, they are pushed to the in-home gateway. Figure 23 shows a basic web page for the consumer preference engine used in the test-bed.

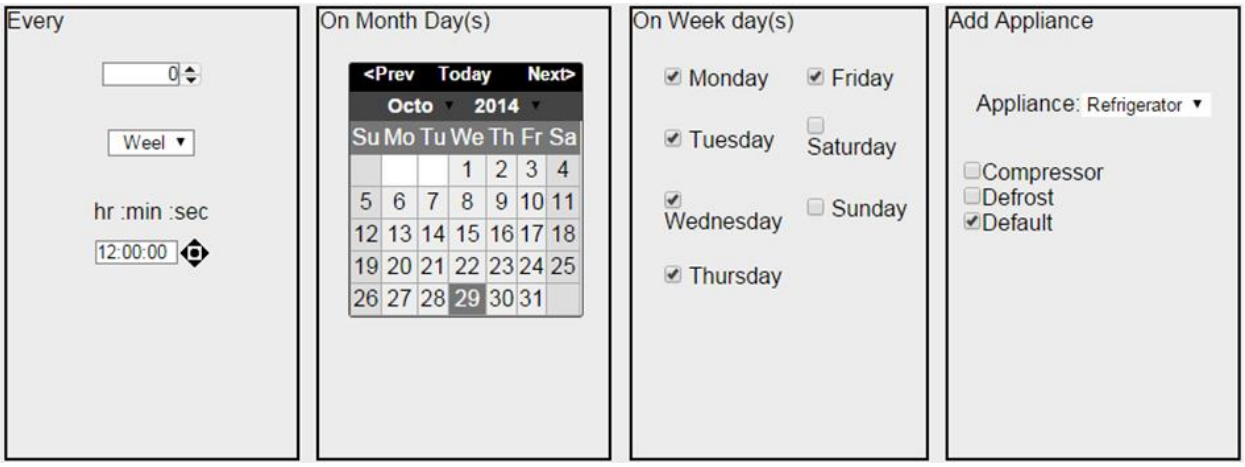


Figure 23. Web interface to the Consumer Preference Engine

The HTML page allows a customer to add an appliance to the preference engine and even select which component can be curtailed; in Figure 23, a user can choose to curtail the function of the refrigerator's compressor, without affecting other functionality. Once an appliance is selected, the user can create a schedule that indicates when the appliance is available for curtailment; users can select the month, day of the week, and/or hour, and set the duration for how long the appliance can curtail during that time. The in-home gateway stores the preferences within the database, using a similar format to the UNIX job scheduler.

Table 5: Sample preference setting

Minute	Hour	Day of Month	Month	Day of Week	Duration (in minutes)	Appliance	Component to Curtail
0	12	*	*	1-5	240	Refrigerator	Any/All

Table above shows a sample entry in the database, which states that for any weekday (Monday to Friday) starting at noon, the refrigerator is available to be curtailed for the next four hours.

In other words, from 12 to 4 pm, Monday to Friday, the refrigerator is permitted to act on a DR signal. The in-home gateway is implemented using a single board computer with Wi-Fi and a ZigBee dongle. It includes a real-time clock and keeps track of time using NTP to connect to a public NTP server. The gateway connects to the main server using SSH, which is left open for secured and encrypted communication; thus allowing a channel for PUSH and PULL interaction methods for data exchange and updates to the firmware.

2.3.2.4. Load/Appliance Controller

The appliance controller comprises a controller and relay that can be connected to a range of appliances operating at 110V or 240V as shown in Figure 24. The controller communicates with the smart gateway and sends appliance control signals to the relay. Its design is similar to the gateway, containing a single board computer with a real-time clock, Wi-Fi, and ZigBee dongle. Its enclosure includes an Ethernet port and a power connector. The relay receives appliance control signals that it uses to manage the internal circuits of the appliance. It encloses a relay module and a microcontroller that is programmed to take commands via Universal Asynchronous Receiver / Transmitter (UART) and adjust the relays accordingly.

The appliance controllers are connected directly to the HAN's appliances using DB9 interface to provide power and UART communications and provide several functions. First, they establish network connectivity between the appliances and the smart in-home gateway using Ethernet, Wi-Fi, and/or ZigBee. The controller also directly modifies the appliance's states and functions to manage the electrical load per the direction of the gateway, in response to a DR event and in compliance with the customer's preferences. Finally, the appliance controller sends updates to the in-home gateway regarding energy consumption

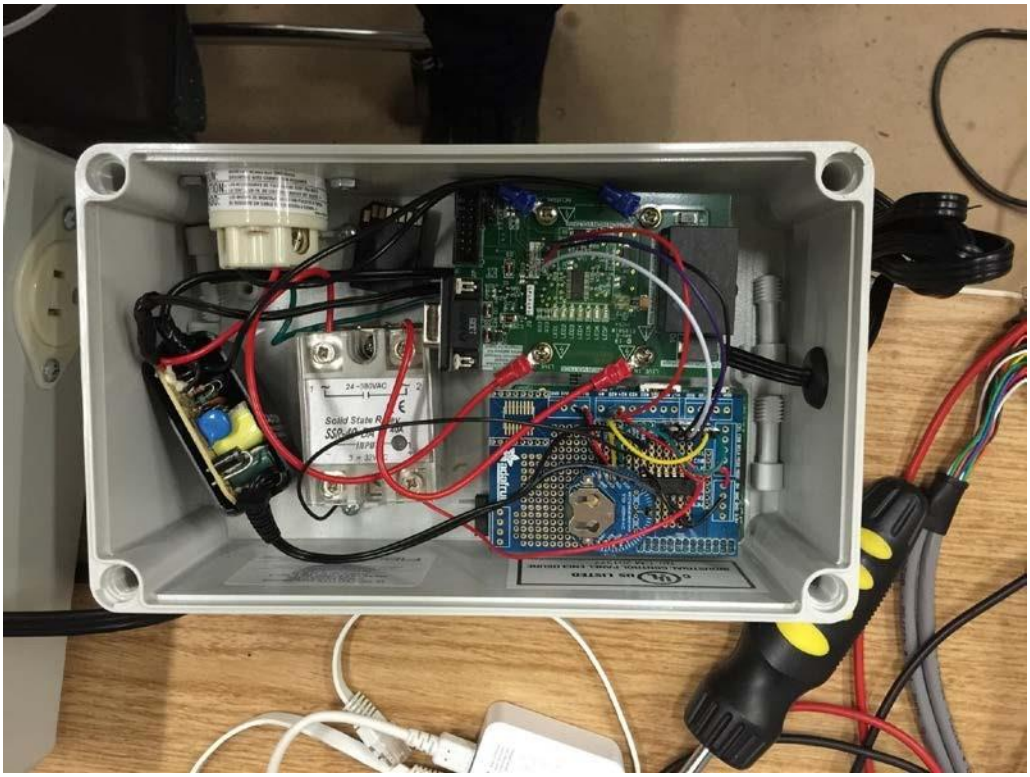


Figure 24. WINSmartGrid Appliance Controller

Salient features of the load/appliance controller

m. Acts as load endpoint of HAN on appliances
n. Provides network connection through wired Ethernet, WiFi, and/or ZigBee
o. Establishes network connectivity with the smart gateway
p. Manages the load per the direction of the smart gateway in response to a DR event and in compliance with customer preference
q. Sends updates of energy consumption data to the smart gateway

The appliance controllers connect directly to the HAN's appliances and have several functions. First, they establish network connectivity between the appliances and the smart in-home gateway using Ethernet, Wi-Fi, and/or ZigBee. The controller also directly modifies the appliance's states and functions to manage the electrical load per the direction of the gateway, in response to a DR event and in compliance with the customer's preferences.

Finally, the appliance controller sends updates to the in-home gateway regarding energy consumption.

The appliance controller comprises a controller and relay. Figure 25 shows these devices connected to and configured for controlling an LED light.



Figure 25. Appliance controller and relay for an LED light

The appliance controller communicates with the in-home smart gateway and sends appliance control signals to the relay. Its design is similar to the gateway, containing a single board computer with a real-time clock, Wi-Fi, and ZigBee dongle. The appliance controller's enclosure includes an Ethernet port and a power connector. Figure 26 shows a schematic of the controller

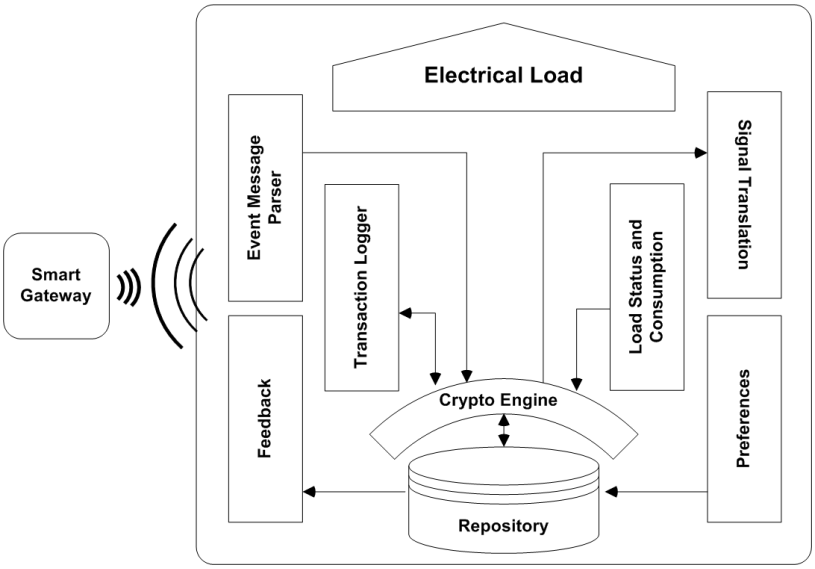


Figure 26. Appliance Controller Architecture

The relay receives appliance control signals that it uses to manage the internal circuits of the appliance. It encloses a relay module and a microcontroller that is programmed to take commands via UART and adjust the relays accordingly. The relay's enclosure includes two connections: one to connect to the appliance, in this case an LED light, and a connector for power and UART communications to the appliance controller's computer. A transformer is used to power all the low voltage controllers (i.e. relay module, microcontroller, and single board computer). The microcontroller is attached to a prototype board for flexibility in the connections among the relay, transformer, and computer.

The single board computer, real time clock, and relay module are mounted and placed in two acrylic plastic boxes designed to prevent physical interference between the controllers and relays. The separation between the relay box and appliance controller isolates the high and low voltage electrical systems, which helps prevent wireless transmission failures caused by close proximity to high voltage, high noise motors, or internal components.

2.3.3. OpenADR Clients on WINSmartGrid

The OpenADR client implemented on WINSmartGrid supports two versions namely, smart client and bridge client. The smart client enables direct integration of OpenADR actions to load management actions of the electrical load. Whereas, the bridge client is an intermediate node in the DRAS to electrical load (HAN node) pipeline and enables automating electrical loads by integrating control units and converting OpenADR event data into load management actions or convert OpenADR events into native protocol control signals for managing the loads.

The OpenADR based AutoDR using WINSmartGRID platform is discussed in detail in the next chapter.

2.3.4. Results

Appliance controllers have been implemented to communicate with and control the internal operations of a refrigerator and dryer, and connect a battery management system to provide energy services for a local power grid. This section describes the experimental setup for each device and how the appliance controllers affect their internal functions.

Refrigerator Implementation



Figure 27: Refrigerator with appliance controller

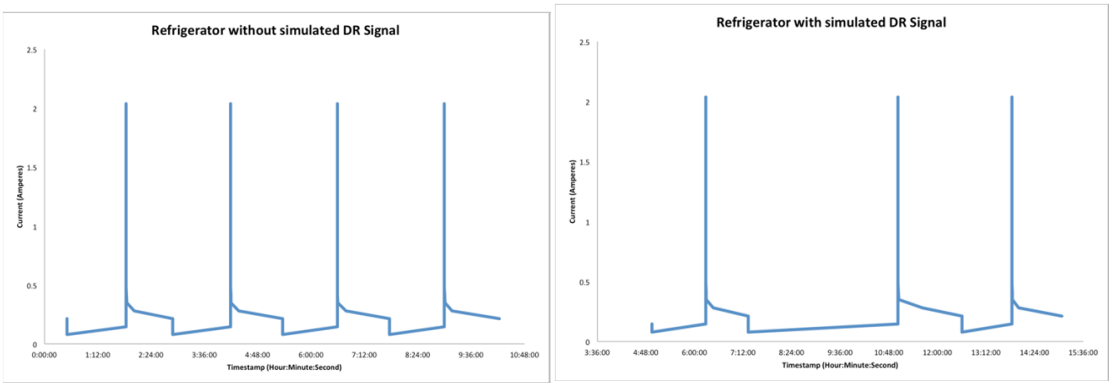


Figure 28: Refrigerator with and without simulated DR signal

Dryer Implementation



Figure 29: Dryer with an appliance controller

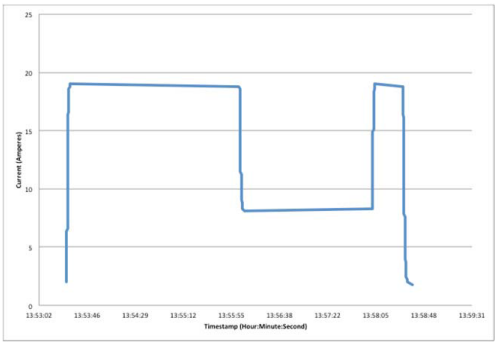


Figure 30: Dryer curtailment after receiving DR signal

HAN, along with the smart gateway and appliance controllers, has been successfully tested for reliability and payload packet designs for the past 15 months. A refrigerator with an appliance controller under the control of the smart gateway has been successfully operated for the past 10 months in graduate apartments of the UCLA DR test bed. The response of the refrigerator to simulated DR events is being tested and the multi-state load curtailment has been consistent.

3.Automated Demand Response

3.1. Automatic Demand Response Architecture

The Automated Demand Response architecture used in the current report describes the elements and their relationships of an automated demand response system that enables reduction in electric load during periods requested by utilities or facilities with minimal to no human involvement. The behind-the-meter load curtailment in homes and buildings is directly initiated by an external signal from the utility or facility through preprogrammed response strategies. This curtailment is made possible by deploying discrete, automated grid- and network-friendly control nodes inside the homes and buildings that convert the utility signals to electricity-use load modifications.

3.2. Open Automated Demand Response

AutoDR is Open Automated Demand Response (OpenADR) communications specification compliant. According to OpenADR Alliance, "OpenADR is an open and interoperable information exchange model, where the message format is standardized so that dynamic price and reliability signals can be delivered in a uniform and interoperable manner amongst the stakeholders"(Ghatikar and Rolf 2011; Piette et al. 2009).

Even though the information exchange model is standardized, automated demand response remains a challenge. The end-to-end grid- and network-friendly automation pipeline is fragile because of a variety of reasons. Chief among them, based on UCLA's research, is the need for costly retrofits to existing homes and buildings. This is caused by the hardware required for protocol translation, and managing heterogeneity of automation controls to prepare for automated demand response controls with OpenADR.

3.3. Demand Response Automation Server (DRAS)

The architecture of the DRAS complies with the OpenADR specification and the interfaces meet the interoperability requirements of an architecture that is integrated and hosted within the UCLA facilities IT infrastructure.

3.4. Architecture

The service-oriented, client-server architecture developed by us supports continuous, two-way, secure messaging between facilities and the participating customers. The client-server service topology of the architecture is as shown in Figure 31.

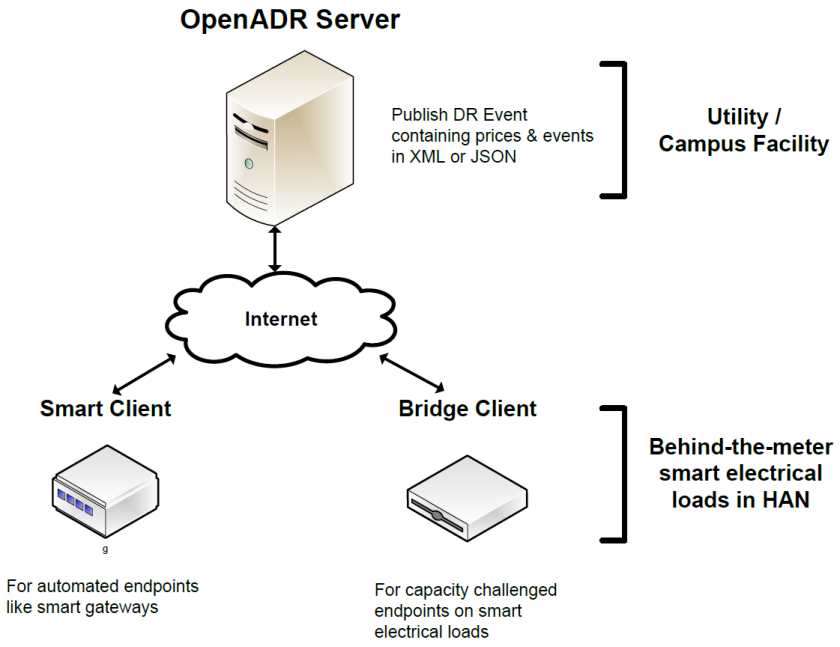


Figure 31 REST Client-Server Service Topology of the Architecture

Important components of the system that support the test-bed are the service-based technology stack, the DRAS server, smart clients, and the bridge clients.

Technology Stack: The AutoDR server-side solution has been implemented using Windows Communication Foundation (WCF), a very flexible, reliable, secure, transacted and interoperable framework from Microsoft that supports building service-oriented applications. The feature being the ability to send data as asynchronous messages from one service endpoint to another and the server-side endpoint can be part of a continuously available service hosted on Internet Information Services (IIS), the web server in Windows environment. The flexibility of creating the messages has been used to package the DR event in XML or JSON by the same service interface. The salient features of the framework for this solution as developed by us are:

- Asynchronous messaging that facilitates fire and forget communication where the client and server need not wait for request-response processes
- Tightly integrated security provided by the authentication and authorization security context to messages
- Demonstrated performance improvement over standard web services
- Cross-platform support where each platform works with its native data type.

WCF provides a unified software platform for developing distributed architecture that is a requirement of AutoDR.

DRAS Server: Manages the DR event information model containing prices and curtailment values. The server delivers the model in XML or *JavaScript Object Notation* (JSON).

Smart Client: Control node of Home Area Network (HAN) with onboard OpenADR client that directly receives and acts on OpenADR signals to initiate changes in electricity consumption.

Bridge Client: Intermediate node of HAN that receives OpenADR signal and converts it into DR event operation modes and statuses that effect changes to the electricity consumption of the electric load.

Features of the architecture are:

- Signaling / Messaging – Facilitate continuous, 2-way, and secure communications
- Signal Translation – Translate DR event information to Internet signals compliant with the customer facility's network and communication technologies.
- Automation – Initiate load change action on receipt of DR activation message utilizing the preprogrammed DR strategies that is selectable and controlled by the customers
- Notification – The timing of notification of the events may be defined by facilities, providing the customers end-use participation strategies

The architecture has two distinct interfaces:

- Utility/Facility interfaces, and
- Customer / DRAS client interfaces

The diagram in Figure 32 depicts the schematic of the DRAS service topology.

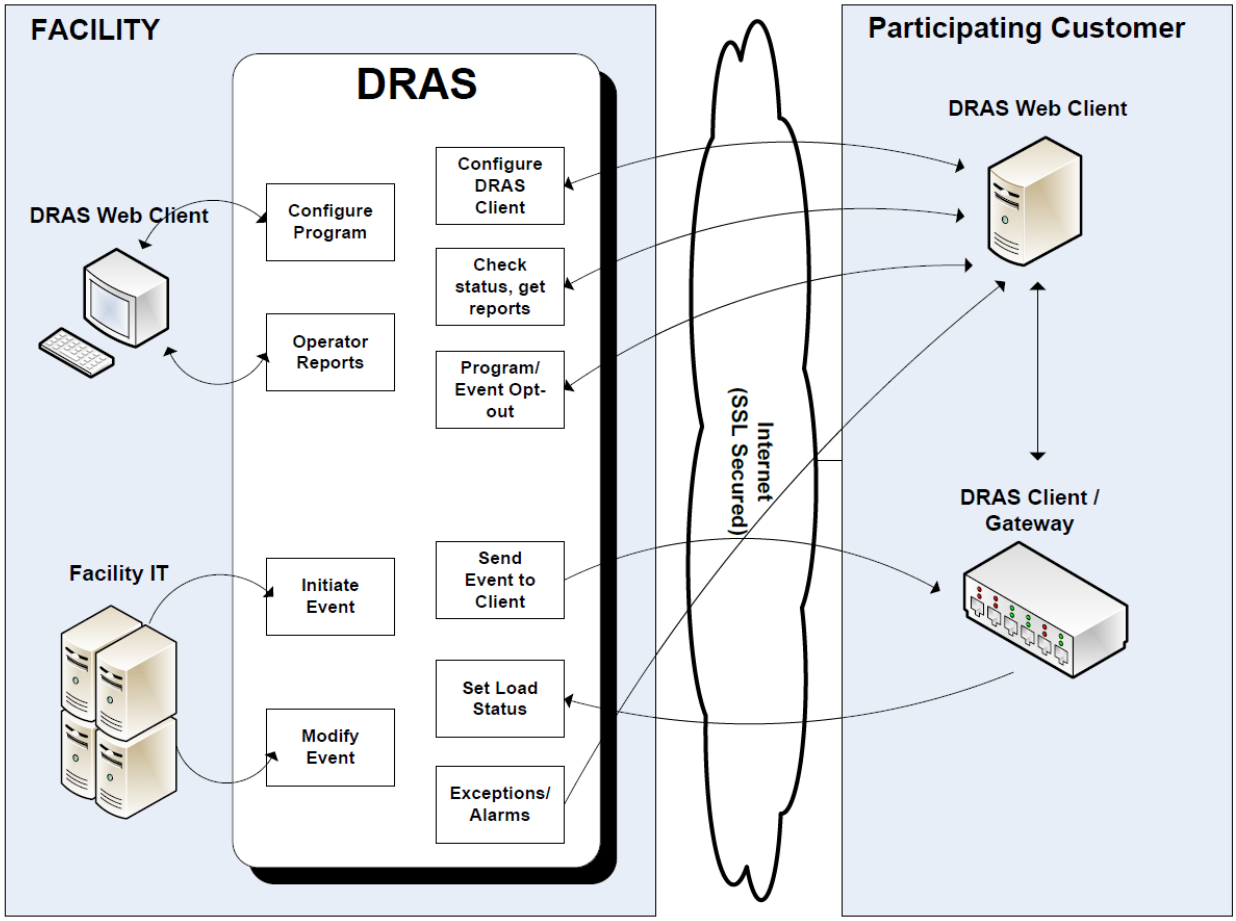


Figure 32 OpenADR-based DRAS Architecture Showing Facility and Customer/DRAS Client Interfaces

This DRAS architecture used by us facilitates communications and messaging between facility IT and the participating customers who manage the consumption of electricity. In this architecture the main messaging payload would be data and information related to emergency and reliability.

3.4.1. Functional Description of the Architecture

The intention of the OpenADR specification is to specify various functions that exist in a complaint DRAS. It is not intended to specify the implementation technology or the details of each of the functions that support the different interfaces as shown in Figure 32. The specification does not require how the information is stored internally or specify the design of the database schemas. The user interface of the interfaces is also implementation specific, whereby it can be customized as per the requirements of the service provider(s) and the planned DR programs.

3.4.2. Overall Functional Requirements

Functionally the DRAS system used complies with the following general requirements:

- The message and data exchanges adhere to security policies to insure all exchanges are authenticated, encrypted and maintain integrity.
- Latency of the DR event sent from server to clients is minimum

- DRAS maintains accurate time within 15 seconds
- Provide for gradual recovery from faults, minimizing data loss

The main subsystems/functions of the DRAS architecture are shown in Figure 33.

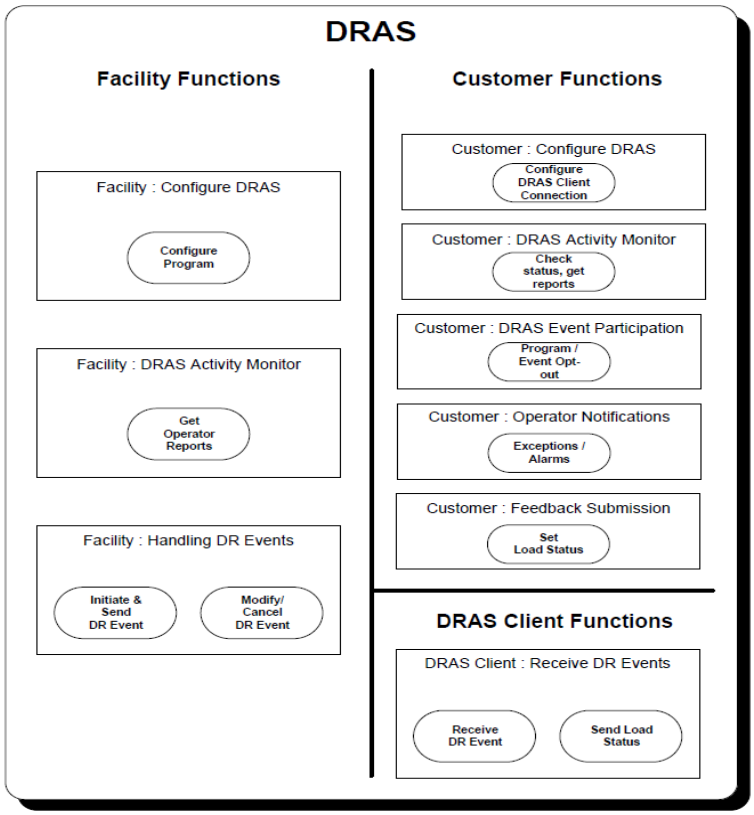


Figure 33 DRAS Sub-Systems and Functions

Utility-side Functions

The following are the functions of the utility/facility-side interface of the DRAS architecture:

1. *Utility DRAS Configuration*: Utility/facility sets up the DR program, and signs up participants to create a customers' record based on the record existing in the CIS for each participating customer. The program information that is included is –
   - Program definition:
     - Schedule – time-of-day, duration, and so forth
     - Type of event (levels) of the DR event
   - Utility assigned account number
   - Participant identification
   - Password for participant

- Location

2. *Utility DRAS Activity Monitor*: Utility operator gets the operation reports as follows -
    - Communication logs
    - Current status of DRAS client
    - Last contact with clients
    - Signal logs
    - Participants manual settings (opt-out status)
    - Event status
3. *Utility DR Events' Handling*: Utility operator schedules and initiates an event. The information sent to DRAS would include –
    - Program type
    - Date and time of event
    - Date and time issued
    - Location
    - Participation list (list of customers/account numbers)

The event-notifier of DRAS sends this information to the registered DRAS clients. The utility/facility operator sometimes decides to modify or cancel an already issued DR event.

Customer-side Functions

The following are the main functions of the customer-side interface of the DRAS architecture:

Customer DRAS Configuration: The customer configures the DRAS program parameters and the DRAS client connection information that would include –

- Participant ID and password
- Contact information (phone number, email)
- DRAS Client communication parameters:
    - DRAS IP address
    - Identification
    - Password
    - IP connection information
    - Polling frequency (if client polls)
- Load reduction potential (load use preferences per time per event level)

- Exception parameters
- Opt-out settings

Customer DRAS Activity Monitor: The DRAS provides the participant the following information -

- Event status
    - Current Outstanding Events
        - Load reduction potential from the aggregated impacted participants
        - Feedback from DRAS clients
    - Event logs

Customer Event Participation: This function enables the customer to opt-in / opt-out of the DR program. The opt-out would be for either the entire DR program or a single event. When in opt- out condition the DR events are not propagated to the DRAS client.

Customer Operator Notifications: DRAS to communicate any exception notification in case of errors or break in operation. These exceptions include machine and platform specific errors and communication failures.

Customer Feedback Submission: The feedback mechanism sends information to DRAS. This mechanism is used to record how the customer responded to the DR event. Data recorded includes –

- Program identifier
- Customer identifier
- Date and time of the event
- Shed data in kW / kWh
- Real-time load
- Specific load reduction (Heating, Lighting, HVAC, Appliances – for opt-in customers)
- Event type

DRAS Client Reception of DR Event: The DRAS client / Gateway propagate the DR event signal to each of the controlled loads for load shed, shift or shape action. The status of the load under the active event is relayed back to the DRAS.

3.5. OpenADR on WINSmartGrid Platform

WINSmartGrid platform used in this project is based on Reconfigurable Wireless Integrated Network Sensors (ReWINS) technology developed in SMERC UCLA (Ramamurthy, Lal et al. 2005; Ramamurthy, Prabhu et al. 2007). ReWINS is a generic smart sensor platform with plug-n- play support for variety of hardware interfaces, payload processing and communications.

Salient features of ReWINS are

- General purpose hardware interface for diverse sensors and actuators that can be customized for an application through firmware downloads
- Data processing infrastructure in the backend to implement APIs and applications

3.6. ReWINS Technology

ReWINS has a modular plug-n-play architecture as shown in the schematic in Figure 34. It has two main components – a sensor interface and a radio frequency (RF) interface. The microcontroller acts as an intelligent interface between them and supports data collection, data processing, and wireless transmissions. The modules are replaceable in the field without disturbing the other modules. The firmware is updatable to support the replaced modules. The updates relate to sensor run-time parameters, microcontroller program variables, and system software modules.

The software stack of the ReWINS consists of three layers as shown in Figure 34:

- Device Driver: directly interfaces with the hardware interface and extracts digital data
- Device Manager: interfaces with the device drivers and exposes a multiple-data channel interface to the firmware layer
- Firmware: synthesizes the data by fusing the data from multiple channels and provides application specific functionalities like real-time performance and data communications protocol with central control unit

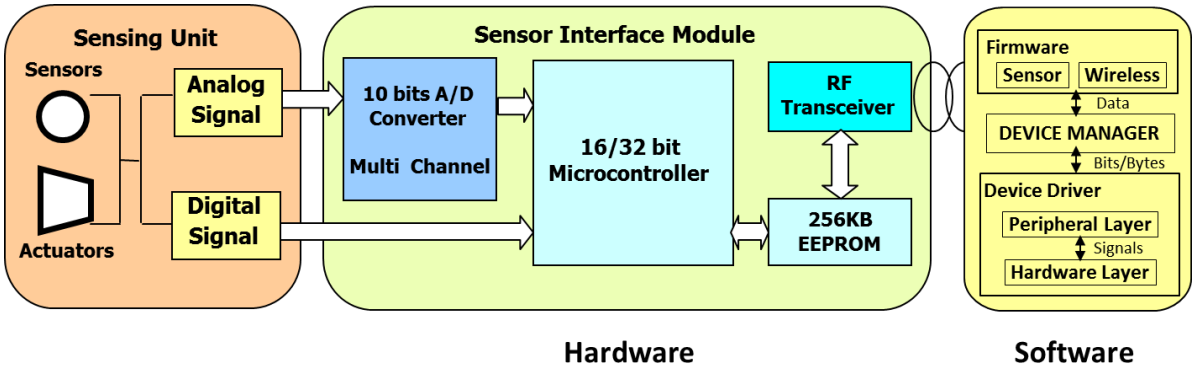


Figure 34 Schematic of ReWINS Platform

One of ReWINS configurations is shown in Figure 35. In this configuration, the platform is setup to monitor an accelerometer, a GPS unit, a temperature sensor, and a humidity sensor. The wireless communications is provided by Bluetooth modem. This configuration was used in demonstrating remote monitoring of perishable goods, such as food products and pharmaceuticals. In this configuration, it logs time, temperature, humidity, acceleration, location and raises alerts based on preset thresholds.

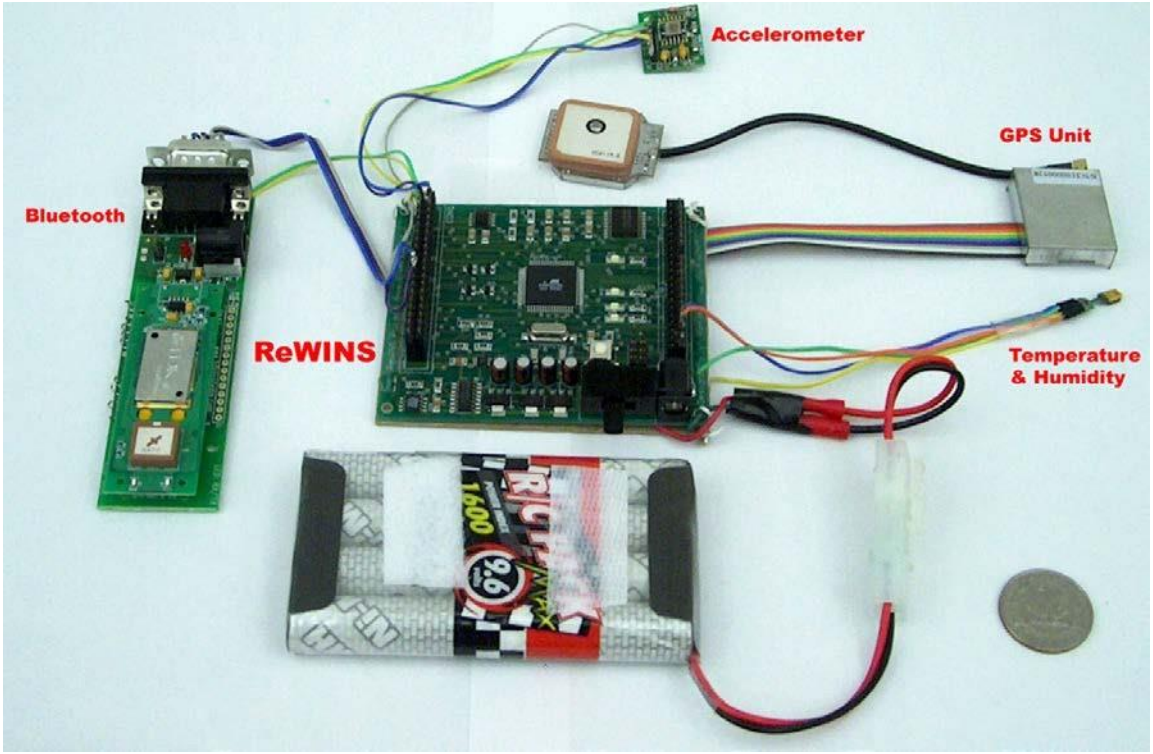


Figure 35 ReWINS Hardware for Monitoring Perishable Assets

3.7. Automatic Demand Reponses Controller

The Automatic demand response controller has been developed on a commercial-off-the-shelf (COTS) single board computer. The battery pack is integrated with the mains connection for the electrical load using 4-pole double throw switch controlled by the controller. The controller is also integrated with an inverter to convert DC power of battery pack to AC power. The OpenADR client resides in this controller and facilitates the direct parsing of the DR event to the battery resource control actions. Figure 36 shows the assembled controller.

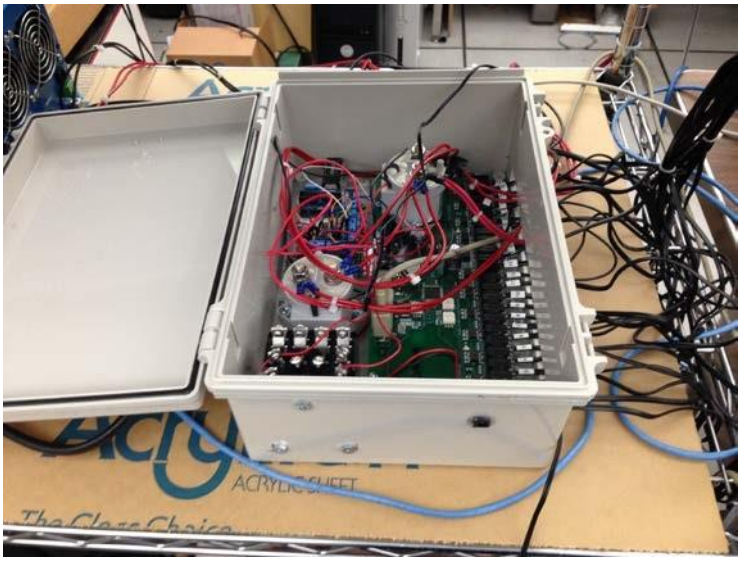


Figure 36 Auto Demand Response Controller with On-Board OpenADR Client

3.8. *DR Event*

On the UCLA campus, most of the buildings and especially the student dormitories are not metered individually hence, DR experiments focus only on load curtailment and not price- responsive event. The DR event is broadcastable in both XML and JSON formats. Figure 37 shows the structure of a DR event generated by DRAS. A DR Event is a signal from the utility or facility to demand response resources requesting load curtailment starting at a specific time, for a specified duration. Appendix A provides sample DR events generated by the DRAS server.

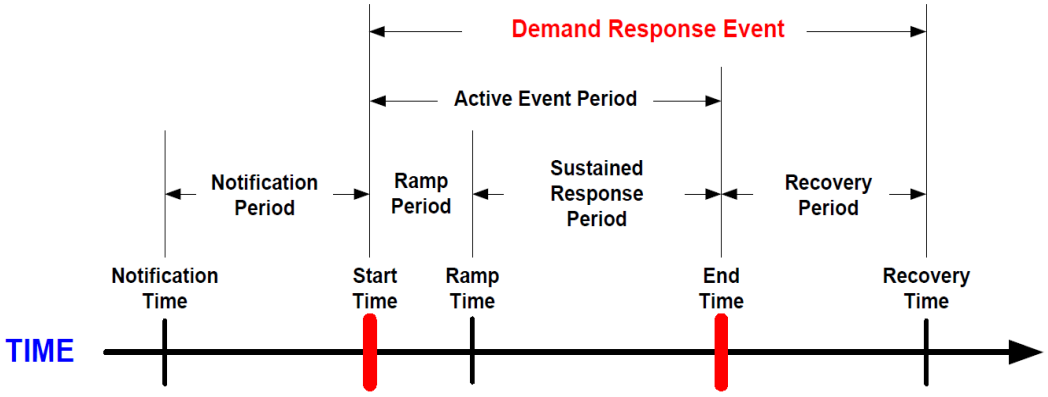


Figure 37 DR Event Structure

3.2.3.1 DR Event Periods

A DR event has distinct periods that demand different actions from the participating loads as per specifications and implemented in the architecture. The periods are:

Notification: is a time prior to the actual start of the event when curtailment is expected, during which time the participation in the event is adjustable by means such as substituting the participating loads and opting out of the event.

Active: is the time when the actual curtailment or change in load profile is expected from the participating resource.

Recovery: is the time during which the participating demand response resource(s) can recover from the curtailment.

3.9. ***Experiments and Results***

To test the DR architecture, DRAS server, OpenADR clients, and different DR programs, the following main tests were run. These test cases were executed concurrently in response to every DR event broadcast by the DRAS server.

- Establishing connection between the DRAS server in SMERC with the smart appliance controllers and smart communicating thermostats

The goal of this test is to examine the connection between the DRAS server and the appliance controllers and thermostats through the OpenADR bridge client, and ensure curtailment actions on receipt of DR event. The curtailment actions are described in Chapter 3.

Results of the tests on AutoDR infrastructure to evaluate system capabilities, communications reliability, and the robustness of the hardware / software interfaces can be summarized as follows:

Table 2: Test Results of DRAS Server Installation

Installation of DRAS server		
Pre-condition: Setup the server for both HTTP and HTTPS network transport		
Step	Description	Result (Success/Failure)
1.	Install the server's service stack in SMERC	Success
2.	Run DRAS server and monitor event logs	Success
3.	Schedule test DR event and log the event operation modes and states	Success

Table 3: Test Results of DRAS to Application Controllers and Thermostats Communications

Test: Establishing connection between the DRAS server in SMERC with the BAC-HD150 adapters and participate in DR events		
Step	Description	Result (Success/Failure)
1.	Create client account for the appliance controllers and thermostats demand	Success
2.	Install bridge OpenADR client on client machine in SMERC	Success

3.	Schedule test DR event with notification period, active period and event retirement	Success
4.	Receive DR event at bridge OpenADR client on appliance controllers and at the thermostats	Success
5.	Schedule DR event	Success
6.	Receive DR event at appliance controller OpenADR clients and the	Success
7.	Execute the current demand response preference settings at each of the appliance controllers and thermostats	Success

3.10. Observations

The AutoDR software service-oriented architecture based on REST model proved well suited for AutoDR applications in most instances. Following are the observations of the architecture:

- Lightweight nature of services proved appropriate for the constrained smart controls like the smart gateway and appliance controller.
- Explicit use of HTTP methods simplified platform and language-independent implementation.
- Client-server requests and responses could be designed to be lightweight reducing network traffic.
- Comparison of DR event and control node responses in XML and JSON showed that JSON format reduced the payload size by 40 to 45 percent, again minimizing network traffic. However, this also implies the existing commonly used format of XML has an inherent payload size disadvantage that could become important in the context of fast DR in which delays need to be kept at a minimum.
- System fidelity was very satisfactory and message exchanges during AutoDR tests between the smart as well as bridge AutoDR clients were complete and reliable.
- One of the observations is pertaining to enterprise security when implementing AutoDR. At various points in the project, certain access types such as TCP ports, service URIs, access through firewalls, proxies and load balancers were blocked due to security reasons and traditional models where the entire network, security and access policies being handled by a single IT department as in the case of private enterprises. Getting access is sometimes an organizational challenge. This challenge is a roadblock for rapid AutoDR scale up, which has more of an open nature than traditional enterprise security.

4. Residential Demand Response Modeling and Simulation

The DR simulation model facilitates generating an energy use model of a residential unit, through aggregation of individual electrical loads strictly satisfying the limitations and constraints of each of the electrical load. The model would take into consideration fixed number of electric appliances, gadgets, and plug-loads of designated electrical ratings in a residential unit.

4.1. Electric Service Model

The simulation model is represented by a proposed XML data model called 'Electric Service Model' (ESM). The hierarchy of the model would include the service size, circuits, and sub-circuits within the breaker panel and the individual breakers, and is called the Electrical Service Objects (ESO). The relationship of ESMs and ESOs and their representation in the smart grid ecosystem is shown in Figure 38.

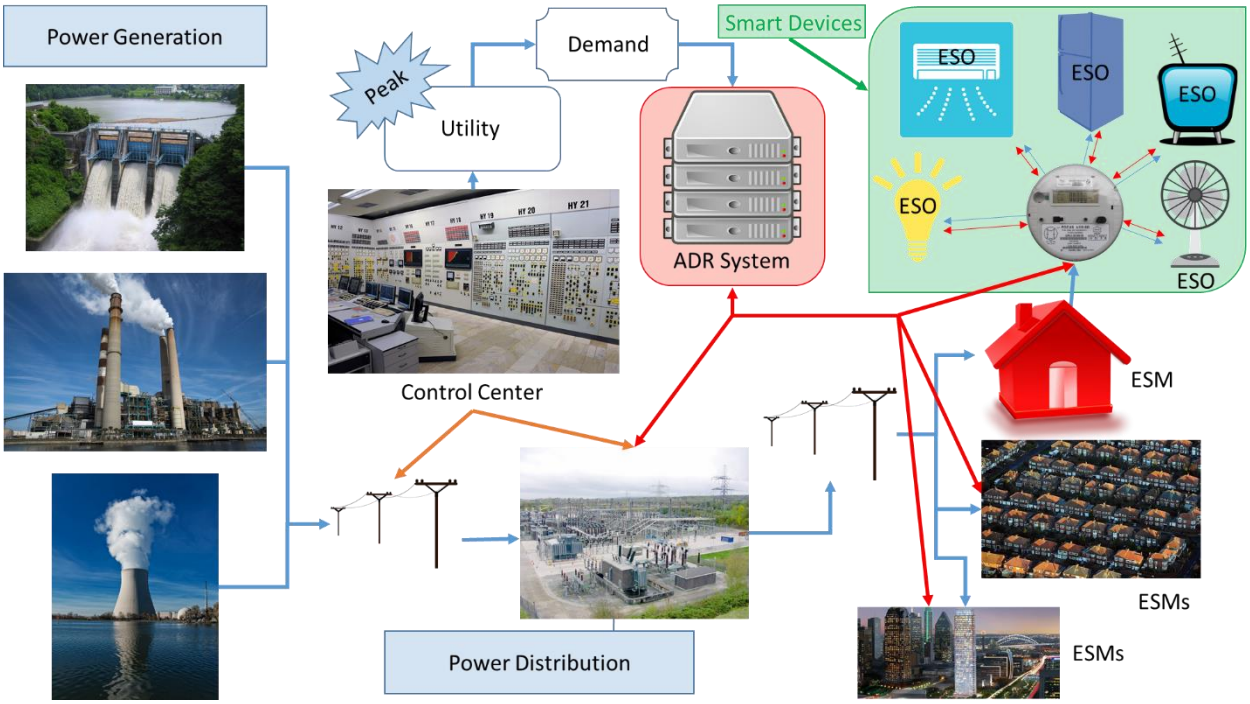


Figure 38 Relationship of ESMs and ESOs in Smart Grid

The motive to develop this model is to investigate a comprehensive extensible representation of smart grid components in a text-based language for describing the characteristics of the components specifications, configurations, status, and diagnostics details. The same model is used to represent end-use preferences of electrical loads and the load's participation in a DR event in this project. The ESM hierarchy with the physical manifestation of the service units is shown in Figure 39.

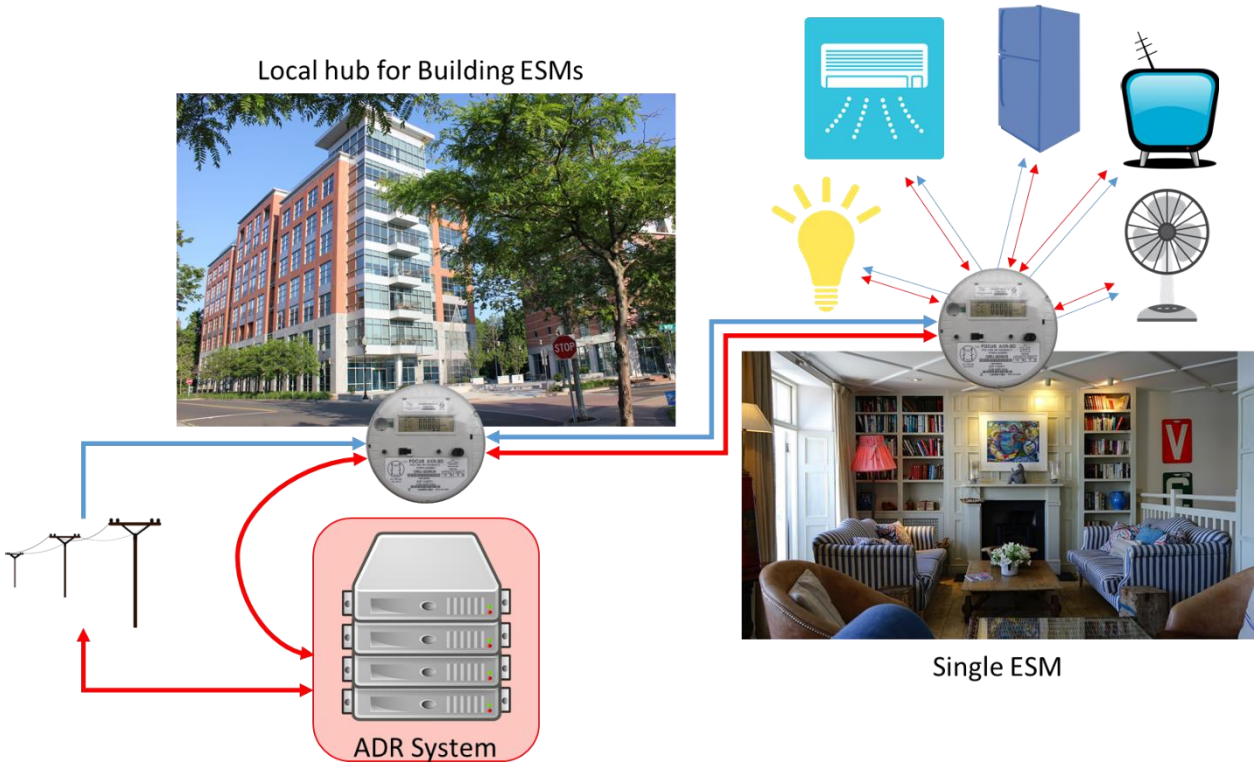


Figure 39 Electrical Service Model Hierarchy

4.2. ***Simulation with three ESMs***

The simulator has three engines namely Randomizer, Priority Randomizer, Priority Timestamp Preference Engine. Once the demand and wattage for the service is available and the user's selection of operation either one of the engines are executed. Figure 40 shows the schematic of the simulator.

Salient points of the three simulator engines are:

Randomizer: It is a basic version of the randomized AutoDR. This AutoDR curtailment engine randomly chooses a participating ESM in the target service area (all participating ESMs) to send the demand signal.

Priority Randomizer: The AutoDR randomizer engine with priority accepts the priority of the devices from the user and stores it with the device model. The curtailment algorithm randomly curtails the individual devices in compliance of the set priorities.

Priority Timestamp Preference Engine: The Priority Timestamp Preference randomizer overcomes the shortcoming of the Priority engine by taking into consideration user's comfort and end-use time preference for a particular device. The algorithm takes into account the curtailment time and comfort preferences which minimize the discomfort which trickles more user-friendliness in the developed AutoDR system. The priority of the system remains the baseline for the curtailment. If the curtailment target is not met even after considering the users preference and comfortless, the user curtails the device based on the priority.

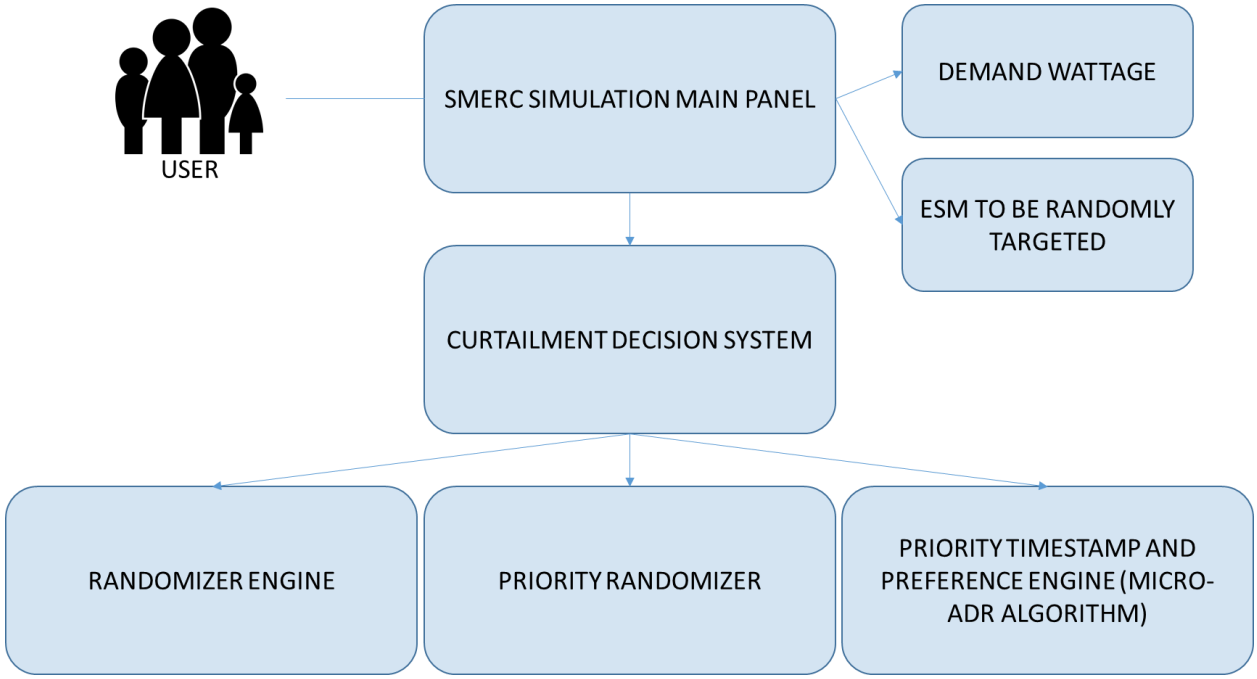


Figure 40 Simulator with the Processing Engines

The following activity diagram in Figure 41, demonstrates the execution of the randomizer engine

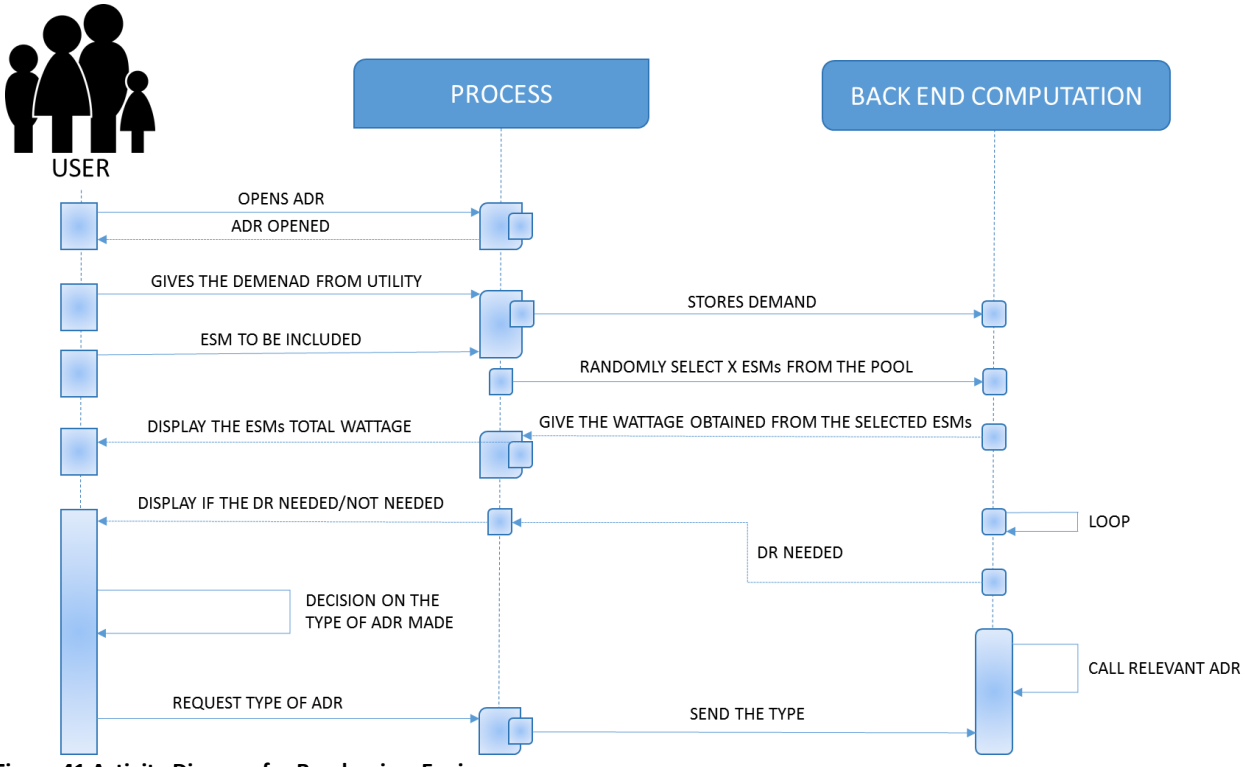


Figure 41 Activity Diagram for Randomizer Engine

The key steps of the simulation are:

1) AutoDR Requests for Demand and ESM count to proceed with the Process.
2) Once the Demand is given, it is sorted and the ESM count number of ESMs is pulled out from XML Database.
3) These XMLs are passed on to the preferred Engine.
4) The Activity is then followed by the Engine of relevant type.

4.3. Observations

The DR modeler and simulator have been successful in modeling residential electrical service and experimenting with DR load curtailment programs. The proposed human readable, XML-based Electric Service Model is capable of representing electrical service, electrical loads, and user priorities and preferences concisely and is successful in supporting the workflow of residential DR. Though it was tested for a campus environment, it appears extensible and scalable to larger communities and utility-scale service base. The load selection engines in response to DR events also provided satisfactory results. These engines need to be tested for larger service bases to ascertain their effectiveness. The engines were successful in selecting optimum loads for a given DR event meeting the user priorities and end-use preferences for the campus sample. The modeler and the selection engines further need to be evaluated in their compatibility for supporting other DR load shed, shape and shift strategies, and price-based programs that are cogent residential DR programs.

5. Project Accomplishments and Conclusion

This report describes the design, implementation and testing of an Automated Demand Response architecture. The research included the following tasks. (1) Design and develop an AutoDR test bed. (2) Design and implement a HAN network and corresponding appliances (3) implement the technology on the test bed in UCLA campus and conduct field tests.

AutoDR technology and software platform developed at SMERC, UCLA was used to investigate Demand Response on UCLA campus. The AutoDR research test bed consists of facility and equipment at graduate student housing, and the SMERC laboratory facilities. These demand response resources were chosen to augment the UCLA DR test bed that already has grid-friendly smart appliances, smart lighting, and EV charging infrastructure, all technologies developed in SMERC under sponsored research from various agencies and organizations. A residential DR modeler and simulator was also developed in this project to assess if a formal data model for residential electric service with the electrical loads, and associated user priorities and preferences can be used to scope target curtailment service in response to a DR event.

The research goal was to develop an Automated Demand Response system that would be compliant with the OpenADR specification, and would permit investigation of different load curtailment DR strategies

and HAN DR programs. The accomplishments of the work done in this project can be summarized under four distinct technology components.

5.1. Automatic Demand Response System

The REST architecture-based AutoDR system has been successfully investigated for both residential and commercial DR programs. A part of this system is the development of the WINSmartGrid OpenADR client platforms using the Reconfigurable Wireless Integrated Network Sensors (ReWINS) technology developed in SMERC. The clients are of two types: Smart Client and Bridge Client. Smart client, which is a platform that can process OpenADR events and directly manage the electrical load, and a bridge client, which is an intermediate node in the network path to receive and process OpenADR events and translate them into a downline control node host protocol or confer smart control to electrical loads.

The clients performed as desired, receiving the OpenADR events and converting them to load curtailment actions directly in the case of storage battery rig and indirectly through translation to BACnet in the case of the HVAC system. These clients are designed for evolution and can be extended to support other electrical loads, control protocols, and DR strategies.

The AutoDR system with these clients was not tested with a large number of nodes in the network as part of research investigation in this project. This would present an interesting environment to prove a network of large number of heterogeneous nodes with variety of control schemes, communication modalities, and DR strategies and programs. This work will be continued utilizing the UCLA DR test bed.

5.2. Residential Demand Response Modeling and Simulation

Availability of a concrete curtailment capacity size for DR dispatch is a preferable service. However, it is very difficult if real-time visibility into the potential participating electrical loads is not available, which often is the case as penetration of two-way communicating smart electrical loads is limited. When smart loads will become prevalent, DR dispatch can become precise with the availability of real-time data. The DR modeler and simulator platform developed as part of this research is targeted as a proof-of-concept towards such a scenario.

With the availability of real-time data from electrical loads, their election of end-use duration and priority, it would be feasible to better assess the potential curtailment capacity in response to a DR event.

To accomplish this, a data model to represent residential units and their electrical loads called Electric Service Model is proposed. The model also facilitates representation of the end-use preference and priority of electric loads. In response to a DR event, the simulator is capable of aggregating electrical loads across multiple residences satisfying the priorities and preferences as curtailment capacity. A conclusion is that selection engines are adept at aggregating loads during DR event runtime by analyzing the prioritized and preferred available loads. This simulator feature can be employed during the active period of an OpenADR event to investigate accuracy of aggregate curtailment capacity to the DR dispatch.

As mentioned earlier, these engines need to be evaluated for large service bases to ascertain their effectiveness, and their compatibility for supporting other DR load shed, shape and shift strategies, and price-based programs.

5.3. Technology Transfer Activities

The objective of the tech transfer activities is to advance the research and technologies developed and explore the value and potential for use in real-world commercial settings. To further the commercialization potential, the following activities were performed:

- ***Industry workshops***: Periodic workshops were held in which LADWP's management and engineers were invited. At these workshops, UCLA's researchers and graduate students showed demonstrations of research, and technology developed to the external visitors. Feedback was received in terms of trends in electric utility sector and such feedback was used in advancing the research.
- ***Industry meetings***: Industry meetings were held one-on-one with individual companies that presented potential synergies with respect to determining how to integrate this project's research ideas with specific vendor technologies to create useful and advanced technologies and applications.
- ***Industry partners program***: The research team held focused workshops with industry partners in which over a dozen vendors participated. These vendors demonstrated how their technologies are used in utility applications to the research team. The vendors also provided an overview about their commercialization process from the vendor perspective. UCLA's commercialization officers attended the workshops and provided insights on UCLA's internal commercialization process. An objective of such focused meetings was to determine how to do technology transfer and to create transfer-ready technologies, and to understand both perspectives – the internal UCLA perspective and external vendor perspective.
- ***Live demonstrations on campus***: The research team has taken some of the research and technology and created live demonstrations on campus. For example, the smart appliances controllers that accept the OpenADR signals are available for demonstration on campus. In the future, such live demonstrations are expected to lead to possible opportunities for technology transfer.

Because of this research project, the research team created AutoDR technologies that are relevant to the commercial world.

GLOSSARY

Term	Definition
Automated Demand Response (AutoDR)	Automatic demand response is the minimal to no human involvement in achieving electricity curtailment in response to utility-side signals
Home Area Network (HAN)	Dedicated network that connects smart electrical loads such as devices and appliances to the Smart Grid and allows them to be automated to interact with utility/ISO control signals
JavaScript Object Notation (JSON)	Lightweight text-based data-interchange format that is easy for people to read and write and easy for machines to generate or parse
Open Automated Demand Response (OpenADR)	A messaging protocol for exchanging price and grid reliability between utilities/ISO and consumers.
Extensible Markup Language (XML)	A standard to describe data that allows a flexible way to create information formats and electronically share structured data over the networks
AC	Alternating Current
Ah	Ampere-Hour
APDU	Application Protocol Data Units
BAS	Building Automation System
BMS	Battery Management System
COTS	Commercial-off-the-shelf
DHP	Ductless Heat Pump
DR	Demand Response
DRAS	Demand Response Automation Server
ESM	Electric Service Model

ESM	Electrical Service Model
ESO	Electrical Service Object
EV	Electric Vehicle
HTTP	Hypertext Transfer Protocols
HVAC	Heating, Ventilation, and Air Conditioning
IP	Internet Protocol
kWh	Kilowatt-Hour
NTP	Network Time Protocol
REST	Representational State Transfer
ReWINS	Reconfigurable Wireless Interface for Networking Sensors
SBC	Single Board Computer
SMERC	Smart Grid Energy Research Center
SSH	Secure Shell
TCP	Transmission Control Protocol
UART	Universal Asynchronous Receiver / Transmitter
UDP	User Datagram Protocol
UPS	Uninterruptible Power Supply
URI	Uniform Resource Identifier
VRF	Variable Refrigerant Flow
WCF	Windows Communications Foundation

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APPENDIX A:

Sample DR Event

These are sample DR events generated by the DRAS server in XML or JSON. They show the different states of the event.

a) DR Event in XML

Notification:

```
<?xml version="1.0" encoding="utf-8" standalone="yes"?>

<p:listOfEventState xmlns:p="http://www.openadr.org/DRAS/EventState">

 <p:eventStates programName="LADWP Demo [03.08.2015]" eventModNumber="0"
eventIdentifier="Client10_Test_345678_906745" drasClientID="dras_client10" eventStateID="1034654074"
schemaVersion="1.0" drasName="UCLA-DRAS 2.5.5" testEvent="false" offLine="false">

<p:simpleDRModeData>

<p:EventStatus>NONE</p:EventStatus>

<p:OperationModeValue>NORMAL</p:OperationModeValue>

<p:currentTime>0.0</p:currentTime>

</p:simpleDRModeData>

</p:eventStates>

</p:listOfEventState>
```

Far state:

```
<?xml version="1.0" encoding="utf-8" standalone="yes"?>

<p:listOfEventState xmlns:p="http://www.openadr.org/DRAS/EventState"
xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
xsi:schemaLocation="http://openadr.lbl.gov/src/1/EventState.xsd">

 <p:eventStates programName="LADWP Demo [03.08.2015]" eventModNumber="0"
eventIdentifier="Client10_Test_345678_906745" drasClientID="dras_client10" eventStateID="1034654074"
schemaVersion="1.0" drasName="UCLA-DRAS 2.5.5" testEvent="false" offLine="false">

<p:simpleDRModeData>

<p:EventStatus>FAR</p:EventStatus>

<p:OperationModeValue>NORMAL</p:OperationModeValue>

<p:currentTime>-60</p:currentTime>

<p:operationModeSchedule>

<p:modeSlot>

<p:OperationModeValue>MODERATE</p:OperationModeValue>
```

<p:modeTimeSlot>0</p:modeTimeSlot>

</p:modeSlot>

</p:operationModeSchedule>

</p:simpleDRModeData>

<p:drEventData>

<p:notificationTime>2015-03-08T22:15:24.24-07:00</p:notificationTime>

<p:startTime>2015-03-08T22:16:24.24-07:00</p:startTime>

<p:endTime>2015-03-08T22:18:24.24-07:00</p:endTime>

<p:eventInfoInstances>

<p:eventInfoTypeID>LOAD_AMOUNT</p:eventInfoTypeID>

<p:eventInfoName>bid</p:eventInfoName>

<p:eventInfoValues>

<p:value>0.0</p:value>

<p:timeOffset>0</p:timeOffset>

</p:eventInfoValues>

<p:eventInfoValues>

<p:value>0.0</p:value>

<p:timeOffset>120</p:timeOffset>

</p:eventInfoValues>

</p:eventInfoInstances>

<p:eventInfoInstances>

<p:eventInfoTypeID>PRICE_ABSOLUTE</p:eventInfoTypeID>

<p:eventInfoName>price</p:eventInfoName>

<p:eventInfoValues>

<p:value>0.0</p:value>

<p:timeOffset>0</p:timeOffset>

</p:eventInfoValues>

<p:eventInfoValues>

<p:value>0.0</p:value>

<p:timeOffset>120</p:timeOffset>

</p:eventInfoValues>

</p:eventInfoInstances>

<p:eventInfoInstances>

<p:eventInfoTypeID>PRICE_MULTIPLE</p:eventInfoTypeID>

<p:eventInfoName>cpp_price</p:eventInfoName>

<p:eventInfoValues>

<p:value>0.0</p:value>

<p:timeOffset>0</p:timeOffset>

</p:eventInfoValues>

<p:eventInfoValues>

<p:value>0.0</p:value>

<p:timeOffset>120</p:timeOffset>

</p:eventInfoValues>

</p:eventInfoInstances>

</p:drEventData>

</p:eventStates>

</p:listOfEventState>

Active State:

<?xml version="1.0" encoding="utf-8" standalone="yes"?>

<p:listOfEventState xmlns:p="http://www.openadr.org/DRAS/EventState"
xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
xsi:schemaLocation="http://openadr.lbl.gov/src/1/EventState.xsd">

<p:eventStates programName="LADWP Demo [03.08.2015]" eventModNumber="0"
eventIdentifier="Client10_Test_345678_906745" drasClientID="dras_client10" eventStateID="1034654074"
schemaVersion="1.0" drasName="UCLA-DRAS 2.5.5" testEvent="false" offLine="false">

<p:simpleDRModeData>

<p:EventStatus>ACTIVE</p:EventStatus>

<p:OperationModeValue>MODERATE</p:OperationModeValue>

<p:currentTime>15</p:currentTime>

<p:operationModeSchedule>

<p:modeSlot>

<p:OperationModeValue>MODERATE</p:OperationModeValue>

<p:modeTimeSlot>0</p:modeTimeSlot>

</p:modeSlot>

</p:operationModeSchedule>

</p:simpleDRModeData>

<p:drEventData>
<p:notificationTime>2015-03-08T22:15:24.24-07:00</p:notificationTime>
<p:startTime>2015-03-08T22:16:24.24-07:00</p:startTime>
<p:endTime>2015-03-08T22:18:24.24-07:00</p:endTime>
<p:eventInfoInstances>
<p:eventInfoTypeID>LOAD_AMOUNT</p:eventInfoTypeID>
<p:eventInfoName>bid</p:eventInfoName>
<p:eventInfoValues>
<p:value>0.0</p:value>
<p:timeOffset>0</p:timeOffset>
</p:eventInfoValues>
<p:eventInfoValues>
<p:value>0.0</p:value>
<p:timeOffset>120</p:timeOffset>
</p:eventInfoValues>
</p:eventInfoInstances>
<p:eventInfoInstances>
<p:eventInfoTypeID>PRICE_ABSOLUTE</p:eventInfoTypeID>
<p:eventInfoName>price</p:eventInfoName>
<p:eventInfoValues>
<p:value>0.0</p:value>
<p:timeOffset>0</p:timeOffset>
</p:eventInfoValues>
<p:eventInfoValues>
<p:value>0.0</p:value>
<p:timeOffset>120</p:timeOffset>
</p:eventInfoValues>
</p:eventInfoInstances>
<p:eventInfoInstances>
<p:eventInfoTypeID>PRICE_MULTIPLE</p:eventInfoTypeID>
<p:eventInfoName>cpp_price</p:eventInfoName>
<p:eventInfoValues>
<p:value>0.0</p:value>

<p:timeOffset>0</p:timeOffset>

</p:eventInfoValues>

<p:eventInfoValues>

<p:value>0.0</p:value>

<p:timeOffset>120</p:timeOffset>

</p:eventInfoValues>

</p:eventInfoInstances>

</p:drEventData>

</p:eventStates>

</p:listOfEventState>

b) DR Event in JSON Notification:


```
{

"p:listOfEventState": {

"@xmlns:p": "http://www.openadr.org/DRAS/EventState",
"p:eventStates": {

"@programName": "LADWP Demo [03.08.2015]",
"@eventModNumber": "0",

"@eventIdentifier": "Client10_Test_345678_906745",
"@drasClientID": "dras_client",

"@eventStateID": "7112038466",

"@schemaVersion": "1.0",

"@drasName": "UCLA-DRAS 2.1.8",

"@testEvent": "false",
"@offLine": "false",
"p:simpleDRModeData": {
"p:EventStatus": "NONE",

"p:OperationModeValue": "NORMAL",
"p:currentTime": "0.0"

}

}

}

}
```


Near State:

```
{

"p:listOfEventState": {

"@xmlns:p": "http://www.openadr.org/DRAS/EventState",
"p:eventStates": {

"@programName": "LADWP Demo [03.08.2015]",
"@eventModNumber": "0",

"@eventIdentifier": "Client10_Test_345678_906745",
"@drasClientID": "dras_client",

"@eventStateID": "7112038466",

"@schemaVersion": "1.0",

"@drasName": "UCLA-DRAS 2.1.8",

"@testEvent": "false",
"@offLine": "false",
"p:simpleDRModeData": {
"p:EventStatus": "NEAR",

"p:OperationModeValue": "NORMAL",
"p:currentTime": "-10",
"p:operationModeSchedule": { "p:modeSlot":
{



"p:OperationModeValue": "HIGH",
"p:modeTimeSlot": "0"

}

}

},

"p:drEventData": {

"p:notificationTime": "2015-03-08T21:42:00-07:00",
"p:startTime": "2015-03-08T21:42:30-07:00",

"p:endTime": "2015-03-08T21:44:30-07:00",

"p:eventInfoInstances": [

{

"p:eventInfoTypeID": "LOAD_AMOUNT",
"p:eventInfoName": "bid", "p:eventInfoValues": [

{

"p:value": "0.0",

"p:timeOffset": "0"

},
```

```
{

"p:value": "0.0",

"p:timeOffset": "120"

}

]

},

{

"p:eventInfoTypeID": "PRICE_ABSOLUTE",
"p:eventInfoName": "price", "p:eventInfoValues": [

{

"p:value": "0.0",

"p:timeOffset": "0"

},

{

"p:value": "0.0",

"p:timeOffset": "120"

}

]

},

{

"p:eventInfoTypeID": "PRICE_MULTIPLE",
"p:eventInfoName": "cpp_price",
"p:eventInfoValues": [

{

"p:value": "0.0",

"p:timeOffset": "0"

},

{

"p:value": "0.0",

"p:timeOffset": "120"

}

]

}

]
```

```
}

}

}

}
```


Active State:


```
{

"p:listOfEventState": {

"@xmlns:p": "http://www.openadr.org/DRAS/EventState",
"p:eventStates": {

"@programName": "LADWP Demo [03.08.2015]",
"@eventModNumber": "0",

"@eventIdentifier": "Client10_Test_345678_906745",
"@drasClientID": "dras_client",



"@eventStateID": "7112038466",

"@schemaVersion": "1.0",

"@drasName": "UCLA-DRAS 2.1.8",

"@testEvent": "false", "@offLine":
"false", "p:simpleDRModeData": {
"p:EventStatus": "ACTIVE",

"p:OperationModeValue": "HIGH",
"p:currentTime": "8",
"p:operationModeSchedule": {
"p:modeSlot": {
"p:OperationModeValue": "HIGH",
"p:modeTimeSlot": "0"

}

}

},

"p:drEventData": {

"p:notificationTime": "2015-03-08T21:42:00-07:00",
"p:startTime": "2015-03-08T21:42:30-07:00",

"p:endTime": "2015-03-08T21:44:30-07:00",

"p:eventInfoInstances": [

{
```

"p:eventInfoTypeID": "LOAD_AMOUNT",
"p:eventInfoName": "bid", "p:eventInfoValues": [

{

"p:value": "0.0",

"p:timeOffset": "0"

},

{

"p:value": "0.0",

"p:timeOffset": "120"

}

]

},

{

"p:eventInfoTypeID": "PRICE_ABSOLUTE",
"p:eventInfoName": "price", "p:eventInfoValues": [

{

"p:value": "0.0",

"p:timeOffset": "0"

},

{

"p:value": "0.0",

"p:timeOffset": "120"

}

]

},

{

"p:eventInfoTypeID": "PRICE_MULTIPLE",
"p:eventInfoName": "cpp_price",
"p:eventInfoValues": [

{

"p:value": "0.0",

"p:timeOffset": "0"

},

{

"p:value": "0.0",

"p:timeOffset": "120"

Appendix AU Internal Process Documents Created

#	**Document**	**Description/Purpose**	**Significance**
1	Meter Lab Test	Process outline meters test requirements and process	Ensure meters are correctly testing before inventory to avoid installing defect meters
2	Generate Meter Fatal Error Report	Instructions to generate a report of meters that have reported a fatal error	Used to identify meters for mitigation or replacement
3	Operator Validation of AMI System - Checklist	Checklist of operational items	List of operational tasks to be performed by Smart Grid Operations Center Operations personnel
4	Check CGR Tunnel Status	Instructions to view the tunnel status of CGRs in CG-NMS	Used to investigate non-communicating CGRs
5	Check HER / ASR Status	Instructions to view the tunnel status of HeadEnd Router in CG-NMS	Used to investigate status of HeadEnd Router
6	Check CG-NMS Server Status	Instructions to view status of CG-NMS application server	Used to investigate status of CG-NMS application server
7	How to Log into K-Grid	Instructions for logging into K-Grid application	Login instructions
8	How to Log into Collection Engine	Instructions for logging into Collection Engine application	Login instructions
9	How to Log into CG-NMS	Instructions for logging into CG-NMS application	Login instructions
10	How to log into Field Pro	Instructions for logging into Field Pro application	Login instructions

11	Unregistered Device Report	Instructions to generate a report of meters that have not registered with the Collection Engine	Used to identify meters for investigation
12	Identify Low Quality RFLAN Health	Instructions to generate a report of meters that have poor connectivity	Used to identify meters for RF mitigation
13	Perform RFLAN Clock Read	Instructions to read the meter RFLAN time	Used to identify meter time issues
14	How to Install Field Pro	Instructions to install Field Po application	Software installation procedures
15	Create Time Synchronization Report	Instructions to generate a report of meters that have reported a time synchronization issue	Used to identify meters for mitigation or replacement
16	How to Install CGDM	Instructions to install CGDM application	Software installation procedures
17	How to Connect to a CGR through CGDM	Instructions to connect with a CGR with the CGDM application	Used for on-site CGR functions
18	How to Read Meter LCD Display	Description of meter LCD displays	Meter display information
19	How to Read Meter Nameplate	Description of meter nameplate information	Meter nameplate information
20	View CGR Events	Instructions for viewing CGR events in CG-NMS	Used for CGR analysis
21	View CGR Running Configuration	Instructions for viewing CGR configurations in CG-NMS	Used for CGR analysis
22	View Work Orders in CG-NMS	Instructions for viewing work orders in CG-NMS	Used for work management
23	View NMS Events (All)	Instructions for viewing application events in CG-NMS	Used for CG-NMS analysis
24	View HER/ASR Events	Instructions for viewing HeadEnd Router events in CG-NMS	Used for CGR analysis

25	View NMS Server Events	Instructions for viewing application server events in CG-NMS	Used for CG-NMS analysis
26	View Database Events	Instructions for viewing database events in CG-NMS	Used for CG-NMS analysis
27	Check CGR Status	Instructions for viewing the current status of a CGR in CG-NMS	Used for monitoring
28	Daily Metrics	Instructions for compiling the Daily Metrics report	Used for reporting
29	CGR Down Notification	Instructions on preparing a Down CGR notification	Used for reporting
30	Filter Dashboard by Cluster	Instructions for performing cluster filtering on the K-Grid dashboard	Used for monitoring
31	Watchlists under MITIGATION Tab	Instructions for creating Watchlists in K-Grid	Used for analytics
32	View Electric Vehicle Details	Instructions for viewing electric vehicle charger meters in K-Grid	Used for reporting
33	Down CGR Spreadsheet	Instructions for updating CGR status tracking spreadsheet	Used for reporting
34	Range Extenders Ping Results Spreadsheet	Instructions for logging Range Extender ping results	Used for reporting
35	RFLAN Monitoring	Instructions to view RFLAN monitoring data in the Collection Engine	Used for reporting
36	RFLAN Health Overview	Instructions to view RFLAN health data in the Collection Engine	Used for reporting
37	Single Node Ping	Instructions for performing a ping on a meter from the Collection Engine	Communications testing

38	Node Group Ping	Instructions for performing pings on a group of meters from the Collection Engine	Communications testing
39	Perform Interactive Read	Instructions to perform an on-demand remote meter read	Used for remote meter functions
40	Meter Re-Authentication	Instructions to re-authenticate a meter remotely	Used for remote meter functions
41	Meter Re-Registration	Instructions to re-register a meter remotely	Used for remote meter functions
42	Load Side Voltage Check	Instructions to determine loadside voltage status in the Collection Engine	Used for remote meter functions
43	Read Disconnect Switch	Instructions for reading the current state of a meter disconnect switch	Used for remote meter functions
44	Read Firmware Versions	Instructions for reading the current firmware version of a meter	Used for remote meter functions
45	Identify CGR Backhaul Communication Method	Instructions to identify backhaul communication type for CGRs	Used for CGR analysis
46	Perform Ping from K-Grid	Instructions for pinging a meter from K-Grid	Used for remote meter functions
47	Perform CGR Ping	Instructions for pinging a CGR from K-Grid	Used for remote meter functions
48	Check Cellular Backhaul Signal Strength	Instructions for viewing cellular signal strength	Used for CGR analysis
49	Perform HER / ASR Ping	Instructions for pinging the HeadEnd Router from CG-MNS	Connectivity testing
50	Perform NMS Server Ping	Instructions for pinging the CG-NMS application server	Connectivity testing

51	View Transformer Monitoring Devices	Instructions for viewing transformer monitoring devices on a map	Used for analytics
52	View Meter Response Rate	Instructions for running meter response rate reports in K-Grid	Used for reporting and analysis
53	View Building Type	Instructions to map meters by building types in K-Grid	Identify customer building type
54	View Customer Type	Instructions to map meters by customer types in K-Grid	Identify/filter customer type
55	Change Layers on Map	Instructions to change map layers in K-Grid	Used for analytics
56	Switch Map Type	Instructions to change map types in K-Grid	Used for analytics
57	View Transformer by Service Type	Instructions to map transformers by service types in K-Grid	Used for analytics
58	View Transformer by Installation Type	Instructions to map transformers by installation types in K-Grid	Used for analytics
59	Display Coordinates	Instructions to view GPS coordinates on K-Grid map	Used for analytics
60	Reset Map Settings	Instructions to reset map settings to default in K-Grid	Used for analytics
61	Display Transformer to Meter Connections	Instructions to display transformer-to-meter connections on a map in K-Grid	Used for analytics
62	Display CGRs on a Map in CG-NMS	Instructions to display CGRs on a map in CG-NMS	Used for monitoring
63	Configure CG-NMS Dashboard	Instructions to customize the CG-NMS dashboard	Used for monitoring
64	Trace Circuit for a Transformer on the Map	Instructions for displaying a transformer circuit in K-Grid	Used for analytics

65	Disconnect Meter through K-Grid	Instructions to perform a meter disconnect function from K-Grid	Used for remote disconnection of a meter
66	Reconnect Meter through K-Grid	Instructions to perform a meter connect function from K-Grid	Used for a remote connection of a meter
67	CGR Down	Instructions for handling CGRs that report as Down	CGR troubleshooting
68	Meter Fatal Error Recovery (OTA)	Instructions for remotely performing a fatal error recovery on a meter	Used for remote meter functions
69	RF Desktop Analysis	Instructions for performing RF desktop analysis	RF analysis and troubleshooting
70	CGR Unheard	Instructions for handling CGRs in an Unheard state	CGR troubleshooting
71	HER / ASR Down	Trouble handling instructions for a Down HeadEnd Router	HER troubleshooting
72	HER / ASR Unheard	Trouble handling instructions for an Unheard HeadEnd Router	HER troubleshooting
73	Mitigate CGR Uptime Issue	Instructions for mitigating CGR Uptime Issue	CGR troubleshooting
74	Handle JM Web Services Error	Trouble handling instructions for Collection Engine web service errors	System troubleshooting
75	Time Adjustment Failure	Instructions for mitigating meter time adjustment failures	Meter troubleshooting
76	Power Outage Notifications	Instructions for analyzing power outage notifications	Data analysis
77	Meter Not Registered	Instructions for handling meters that are not registered with the Collection Engine	Meter troubleshooting
78	Non-Fatal Error 1	Non-Fatal Error 1 description and handling instructions	Used for meter error handling

79	Non-Fatal Error 2	Non-Fatal Error 2 description and handling instructions	Used for meter error handling
80	Non-Fatal Error 3	Non-Fatal Error 3 description and handling instructions	Used for meter error handling
81	Non-Fatal Error 4	Non-Fatal Error 4 description and handling instructions	Used for meter error handling
82	Non-Fatal Error 5	Non-Fatal Error 5 description and handling instructions	Used for meter error handling
83	Non-Fatal Error 6	Non-Fatal Error 6 description and handling instructions	Used for meter error handling
84	Fatal Error 1	Fatal Error 1 description and handling instructions	Used for meter error handling
85	Fatal Error 2	Fatal Error 2 description and handling instructions	Used for meter error handling
86	Fatal Error 3	Fatal Error 3 description and handling instructions	Used for meter error handling
87	Fatal Error 4	Fatal Error 4 description and handling instructions	Used for meter error handling
88	Fatal Error 5	Fatal Error 5 description and handling instructions	Used for meter error handling
89	Fatal Error 6	Fatal Error 6 description and handling instructions	Used for meter error handling
90	Fatal Error 7	Fatal Error 7 description and handling instructions	Used for meter error handling
91	Blank Display	Blank Display description and handling instructions	Used for meter error handling
92	On-Site Cannot Communicate with Meter	Instructions for troubleshooting optical communication issues	Used for on-site meter functions
93	Reset Comm Module	Instructions to perform a communication module reset on a meter	Used for on-site meter functions

94	Register with Host	Instructions to register a meter with the Collection Engine	Used for on-site meter functions
95	Force Time Sync	Instructions to force synchronize the meter time with the network	Used for on-site meter functions
96	View Event Log	Instructions for viewing the event log on a meter	Used for on-site meter functions
97	View Neighbor List	Instructions to view a meter's RF neighbor list	Used for on-site meter functions
98	Meter in RFLAN Level 0 Condition	RFLAN 0 description and handling instructions	Used for meter error handling
99	Deregister from Host	Instructions to de-register a meter from the Collection Engine	Used for on-site meter functions
100	Disconnect Meter	Instructions to operation a meter service switch via the optical port	Used for on-site meter functions
101	Connect Meter	Instructions to operation a meter service switch via the optical port	Used for on-site meter functions
102	Connect Meter with Intervention	Instructions to operation a meter service switch (with intervention) via the optical port	Used for on-site meter functions
103	Reset Demand Registers	Instructions for resetting demand registers on a meter	Used for on-site meter functions
104	Reset Billing Registers	Instructions for resetting billing registers on a meter	Used for on-site meter functions
105	Reset Activity Status	Instructions for resetting activity status on a meter	Used for on-site meter functions
106	Reset Inversion Tamper	Instructions for resetting inversion tamper counter on a meter	Used for on-site meter functions

107	Reset Removal Tamper	Instructions for resetting removal tamper counter on a meter	Used for on-site meter functions
108	Clear All Meter Data	Instructions for clearing all data on a meter	Used for on-site meter functions
109	Create Data File	Instructions for creating a meter data file	Used for on-site meter functions
110	Fatal Error Recovery	Instructions for performing a fatal error recovery on a meter	Used for on-site meter functions
111	How to Install or Replace Battery Backup Unit on CGR	Instructions to install or replace a Battery Backup Unit in a CGR	Used for on-site CGR maintenance
112	Collection Engine Upgrade	Instructions to upgrade Collection Engine	Used for application upgrades
113	Certicom Upgrade	Instructions to upgrade the Certicom appliance	Used for application upgrades
114	Upgrade CG NMS	Instructions to upgrade CG-NMS	Used for application upgrades
115	Upgrade CGR Firmware	Instructions to upgrade CGR firmware	Used for firmware upgrades
116	Delete Future Dated Events in CG-NMS	Instructions for deleting future-dated events in CG-NMS	Used for application maintenance
117	Remote Meter Configuration Re-Programming	Instructions to perform a configuration change on a meter from the Collection Engine	Configuration management
118	Add CGRs to CG-NMS	Instructions for adding a CGR to CG-NMS	Used for CGR maintenance
119	Remove CGRs from CG-NMS	Instructions for removing a CGR to CG-NMS	Used for CGR maintenance
120	Configure and Activate New CGR	Instructions to configure and activate a new CGR	Used for CGR maintenance
121	Generating Reports from WMIS	Instructions to generate reports in WMIS	Used for reporting and analysis

122	Meter Return Material Authorization (RMA)	Instructions for RMA handling of a meter	Used to RMA meters
123	CGR Return Material Authorization (RMA)	Instructions for RMA handling of a CGR	Used to RMA CGRs
124	Charging the MiEV Vehicle	Instructions for charging a MiEV vehicle in the Garage of the Future	EV Vehicle charging instructions
125	Discharging the MiEV Vehicle	Instructions for discharging a MiEV vehicle in the Garage of the Future	EV Vehicle discharging instructions
126	Solar Inverter AC Switch Connect/Disconnect	Instructions for connecting and disconnecting the solar inverter in the Garage of the Future	Solar Inverter AC Switch connect/disconnect instructions
127	Run Monthly WMIS Report	Instructions to run Installed Meters report in WMIS	Used to identify installed and removed AMI meters
128	Run Monthly Power Outage Report	Instructions to run the Power Outage report	Used for Department of Energy reporting and OMS data validation
129	Run Monthly Interrogation Jobs report	Instructions to run the Interrogation report	Used for Department of Energy reporting
130	CSR training Messages for SmartPower Partners	Training messages	Steamline response
131	News You Can Use Smart Grid LA for CSRs	Notifications for CSRs	Inform CSRS with training/new information
132	Recognizing Smart Grid Meters Guide for CCC CSRs	How to recognize smart meters	Process inquiry effectively
133	Smart Grid LA Call Center Response Scenario Templates	How to respond to customers	Improve customer satisfaction/reduce issue
134	Smart Grid LA Call Center Standard Operating Procedures	Reference operating procedures	Training reference

135	Smart Grid LA Call Center Training Deck LADWP CCC Training	Reference training	Training reference
136	Smart Grid LA Call Center Lessons Learned White Paper	Share lessons learned	Improve future implementation
137	Smart Grid LA Call Log Customer Inquiry Data	Instruction on how to handle customer inquiry data	Protect sensitive data
138	Smart Grid LA Smart Meter Opt-Out Process	Process on how to handle smart meter opt-out	Effectively process opt-out to avoid customer dissatisfaction which may lead to negative Smart Grid publicity, financial claims, legal issues.
140	IPTable Configuration Procedures for CSFW	Procedures for firewall configuration	To configure CS Firewall
141	Delivery Description	Describe informally the part of the DDR March 31, 2014 delivery that be used for demonstration	Demonstrates a simple, operationally relevant scenario for DDR execution.
142	Integration of SGRDP Containment Capabilities into SGRDP	Demonstrates the ability to manage and control the flow of data across zones within the SGRDP and to and from sites external to the SGRDP	Protect the integrity of systems and data within the SGRDP
143	SGRDP Demonstration Reports on Component Testing and Modeling	Describe Component testing and modeling demonstrations	Provide insights will eventually be used by the DDR components to generate assessment of situational awareness and to plan remediation actions for diagnosed failures

144	DDR August 2014 Integration of SGRDP Detection & Diagnosis – Basic	SGRDP Report on Integration of Diagnosis and Remediation within the SGRDP	Ability to diagnose problems within the smart grid demonstration, especially with respect to attacks on system components, and to initiate remediation to mitigate the impact of such attacks and failures.
145	SGRDP Report on Integration of Basic Detectors within the DDR Cyber Security Components	Integration of Basic Detectors within the DDR Cyber Security Components	Focused on the ability to detect anomalous and routine network and host events on routers and hosts running smart grid demonstration components, and record such events in the Computer Security Database.
146	Integration of SGRDP Detection – Basic	SGRDP CS Integration of Detection	The work described in this document maps to SGRDP Statement of Program Objectives (SOPO) item 3.5.4.1 "Grid resilience against cyber attacks".
147	Basic DDR Component Testing	Describe the Cyber Security (CS) unit (aka component-level) testing performed on basic Detection/Diagnosis/Response (DDR) capabilities developed to date. The CS Top-Level Test Plan (dated May 13, 2013) describes the overall test plan	Supports item 3.5.4.1 - “Grid resilience against cyber attacks” in the Statement of Program Objectives (SOPO).
148	Document Process Cost	Provide instructions on how to collect project cost data and record project expenditure.	Capture project cost to report on project expenditure to DoE on Federal awards and for project cost control

149	Update/Track Budget Expenditure	Track budget	Capture project cost to report on project expenditure to DoE on Federal awards and for project cost control
150	Track Contract Expenditure and Task Order Assignments	Track contractual expense against task order	Ensure invoices are within task order budget
151	Review and Track Contractual Expense	Checklist for invoice review	Ensure invoices have correct information
152	Task Order Amendment	Provide instructions on how to update the task order amendment tracker.	Track changes and status on amendments to task orders
153	Communication Log	Provide instructions on when and how to update and use the Communication Log.	Capture important status and actions for follow ups
154	SCPPA Overview	Provide instructions on how to update the SCPPA expense tracker	Track payment/invoices received from SCPPA/vendors
155	Contract Reconciliation	Provide instructions on how to perform contract reconciliation.	Ensure invoices are reconciled with contract budget
156	Risk Log	Provide instructions on how to update the Risk Log.	Capture risks on the project for DoE reporting and document lessons learned
157	TO create/modify	Provide instructions on how to create/modify a task order	Create/manage control for contractual expense
158	Organization of Contractual Binders	Provide instructions on how to organize contractual binders	Streamline filing and expediture references for contractual expense
159	Desktop Reference	Provide instructions on how to set up printer/scanner/fileshare permission.	Configure contractors' device to network devices to support project
160	Change order creation	Provide instructions on how to create change order	Streamline changes and quality control

161	Decision Tracker	Provide instructions on when and how to update the decision tracker.	Capture decisions impacting deliverables and future processes
162	Publication	Provide instructions on how to process publications for review and submit conference paper.	Obtain pertainent information to submit to DoE on Federal funded projects
163	Data Collection	Provide instructions on how to collect and track data	Capture Data Collection status
164	SF425	Provide instructions on how to update Standard Form (SF) 425	Report quarterly expenditure to DoE on projects receiving Federal grant
165	DoE Progress Report	Provide instructions on how to complete report	Streamline changes and quality control
166	Build Metrics	Provide instructions on how to update Build Metrics Report	Report quarterly Build Metrics to DoE on projects receiving Federal grant
167	Data Collection DR USC Engine Log	Provide instructions on how to collect and track data collection for SGRDP on DR USC engine log	Data Collection
168	Data Collection DRAS	Provide instructions on how to collect and track data collection for SGRDP on DR Events from DRAS at USC	Data Collection

Appendix AV Publications/Conference Papers Written

The following publications and/or conference papers were released under the award:

Co-Authored by JPL & USC

Anas Almajali, Eric Rice, Arun Viswanathan, Kymie Tan, Clifford Neuman. A Systems Approach to Analyzing Cyber-Physical Threats in the Smart Grid. In IEEE Smart Grid Communications Conference (IEEE SmartGridComm), Vancouver, Canada, October 2013.

Arun Viswanathan, Kymie Tan, Clifford Neuman. Deconstructing the Assessment of Anomaly-based Intrusion Detectors for Critical Applications. Proceedings of Research in Attacks, Intrusions and Defenses (RAID) Symposium, St. Lucia, October 2013.

Clifford Neuman, Kymie Tan, Mediating Cyber and Physical Threat Propagation in Security Smart Grid Architectures. Proceedings of the 2nd International Conference on Smart Grid Communications (IEEE SmartGridComm), Brussels, October 2011.

USC

Anas AlMajali, Arun Viswanathan, Clifford Neuman. Analyzing Resiliency of the Smart Grid Communication Architectures Under Cyber Attack. Proceeding CSET'12 Proceedings of the 5th USENIX conference on Cyber Security Experimentation and Test, USENIX Association Berkeley, USC, August 2012.

Tatyana Ryutov, Anas AlMajali, Clifford Neuman. Security Policies for Mitigating the Risk of Load Altering Attacks on Smart Grid Systems. Proceedings of the 2015 Workshop on Modeling and Simulation of Cyber-Physical Energy Systems (MSCPES) (IEEE), Seattle, April 2015.

Sanmukh R. Kuppannagari, Rajgopal Kannan, Charalampos Chelmis, Arash S. Tehrani, and Viktor K. Prasanna, Optimal Customer Targeting for Sustainable Demand Response in Smart Grids, International Conference on Computational Science, 2016.

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Appendix AW Smart Charging and Demonstration Results

Smart Grid Regional Demonstration Program

UCLA Electrical Vehicle Integration Project

Final Report on

Smart Charging and Demonstration Results

DOE award number: DE-OE0000192

Recipient name: The Regents of the University of California (UCLA)

Principle investigator: Rajit Gadh, Ph.D.

Consortium/team members: Peter Chu, Ph.D.

UCLA Smart Grid Energy Research Center

07/31/2016

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Notice:

The information included in this report and its related Use Case reports has been filed with US patent and trademark office:

Accepted:

1. R. Gadh, S. Mal, S. Prabhu, C. Chu, J. Panchal, O. Sheikh, C. Chung, L. He, B. Xiao, Y. Shi, "Smart Electric Vehicle (EV) charging and grid integration apparatus and methods" – US 2013/0179061 a1 – UC-2010-903-2-LA, , Publication number US9026347 B2
2. R. Gadh, C. Chung, L. Qi, C. Chu, "Power control apparatus and methods for electric vehicles" – UC-2013-146-2-LA, Publication number US20140062401 A1

Pending:

1. R. Gadh, S. Prabhu, C. Chu, J. Panchal, O. Sheikh, C. Chung, S. Mal, "WinsmartEV systems and methods" – UC-2011-705-1-LA,
2. R. Gadh, S. Prabhu, C. Chu, O. Sheikh, C. Chung, J. Chynoweth, A. Chattophadhyay, "Intelligent electric vehicle charging system" – UC-2012-057-2_FP-LA
3. R. Gadh, C. Chung, L. Qi, C. Chu, "Network based management for multiplexed electric vehicle charging" – US 2013/0154561 A1 - UC-2012-224-2-LA
4. R. Gadh, C. Chu, C. Chung, J. Chynoweth, L. Qi, A. Shepelev, "SMERC EV charging control system" – UC-2012-644-1-LA
5. R. Gadh, H. Nazaripouya, C. Chu, "Battery energy storage control system" - UC-2016-213-1-LA
6. R. Gadh, B. Wang, L. Qiu, T. Zhang, C. Chung, C. Chu, "Multi-layer Electric Vehicle Energy Management System with Customized Data Models" – UC-2016-957

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1. Overview

The UCLA Electrical Vehicle (EV) and Renewable Integration Project, as part of DOE's Smart Grid Regional Demonstration Project (SGRDP), is focused on researching the latest electrical vehicle related technologies and communication networks to create a flexible Smart Charging Network to run tests and experiments that integrate monitoring and control of EV charging stations, renewable energy, energy storage devices, and vehicle to grid demonstrations. The overall objective of this project is to reduce energy cost and usage and to increase the stability of local power system by managing the charging operations of the EVs, renewable energy and energy storage systems. To achieve this goal, various technologies were adopted to implement the functional requirements of each Use Case. Along with research and development conducted in UCLA Smart Grid Energy Research Center (SMERC), the following major systems are required to conduct demonstrations in each use case:

1. WINSmartEV™ Smart Charging infrastructure
2. SMERC V2G System – vehicle to grid
3. SMERC BESS System – battery energy storage system
4. SMERC SCC – Super Control Center energy, management system

WINSmartEV™ is a smart grid wireless system platform that was used as a testbed to experiment with various network configuration and scheduling algorithms. Demonstrations were built upon this platform to collect data for further analysis. WINSmartEV™ was developed using the technologies developed from WINSmartGrid™. WINSmartGrid™ is a sensing and controlling network architecture that is developed for Smart Grid applications. Details about WINSmartEV™ is presented in section 2 in this report.

SMERC V2G System is a power electronics system that enables an EV to backfeed its battery power into the power grid. Current SMERC V2G system utilizes CHAdeMO port from Mitsubishi –iMiEV to control back feed power. This system is described in detail in section 3 in this report.

SMERC BESS system is a battery power management system that control and monitor the Li-ion battery energy storage system. It supports voltage regulation, reactive power compensation, solar power smoothing and peak demand balancing. This is presented in section 4 in this report.

SMERC SCC is an energy management system that monitor and control various components in a microgrid system. It allows integration of EV Charging, Solar Power, and Energy storage system as well as demand response events. The SCC is presented in section 5 in this report.

1.1. Executive Summary

UCLA Smart Grid Energy Research Center (SMERC) take pride in the achievement accomplished in this project. The following is a list of key achievements:

- Deployed **191** smart EV charging points with **269** EV participants and a total of **25** GB of data for research and analysis under this project.
- Implemented smart EV charging stations with current throttling and multiplexing capability.
- Implemented WinSmartEV™ platform for integration and scheduling algorithms.

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- Implemented V2G system with Mitsubishi MiEV Power box for back-feed operation.
- Integrated BESS, PV and DC Fast Charger (DCFC) for load balancing and power management.
- Published **28** journal/ conference papers, **2** accepted patents and **4** pending patents.

UCLA SMERC continues to make progress on this project with active project demonstration, data collection, data analysis and publication of research results based on the data obtained. Research is ongoing in the development of optimizing EV charging scheduling depending upon various inputs such as user preference, grid status, solar panel output, integration of BESS systems and demand response events. The UCLA EV team continues to study & compare a variety of EV network technologies, perform appropriate & related research, as well as continue to perform the demonstrations in this project.

The following is a list of prominent benefits to power and EV industry as a result from this demonstration project.

- The unique current throttling feature of the charger created in this project allows for flexible power management schema to increase power quality and grid stability.
- The multiplexing features along with scheduling algorithms maximized and optimized usage of existing power circuits
- The implemented WINSmartEV^{TM} platform allows rapid integration of various components such as V2G, BESs, PV and DCFC for power management.
- The lessons learned and best practice identified in each Use Case along with the amount of data collected and EV user participation provide valuable reference for future large scale EV charger deployment.

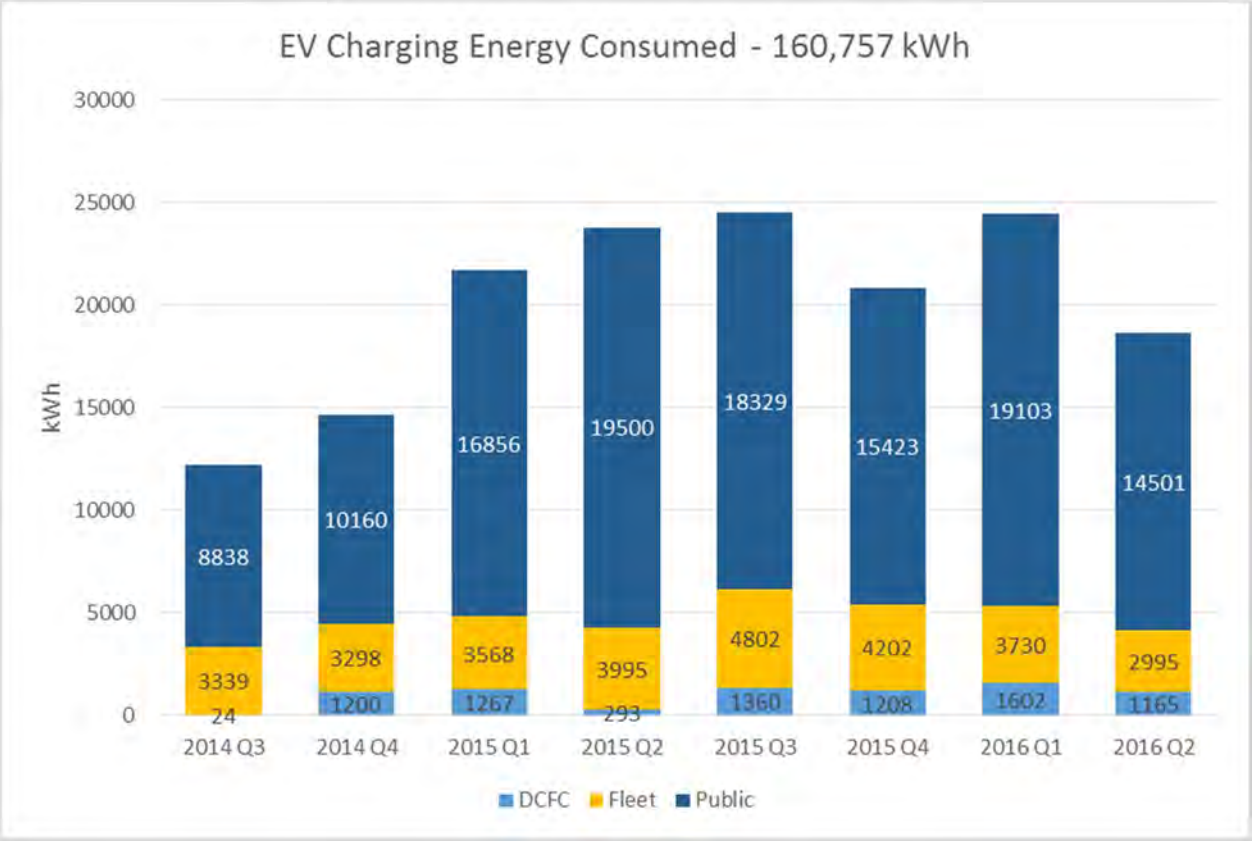
The following charts present a high level overview of EV charging stations deployed in this project, total Energy consumed by EV charging, total charging sessions during the data collection period of this project (7/1/2014 – 6/30/2016). Only charging sessions which consumed more than 0.1 kWh were considered as valid charging session and were included in the statistics.

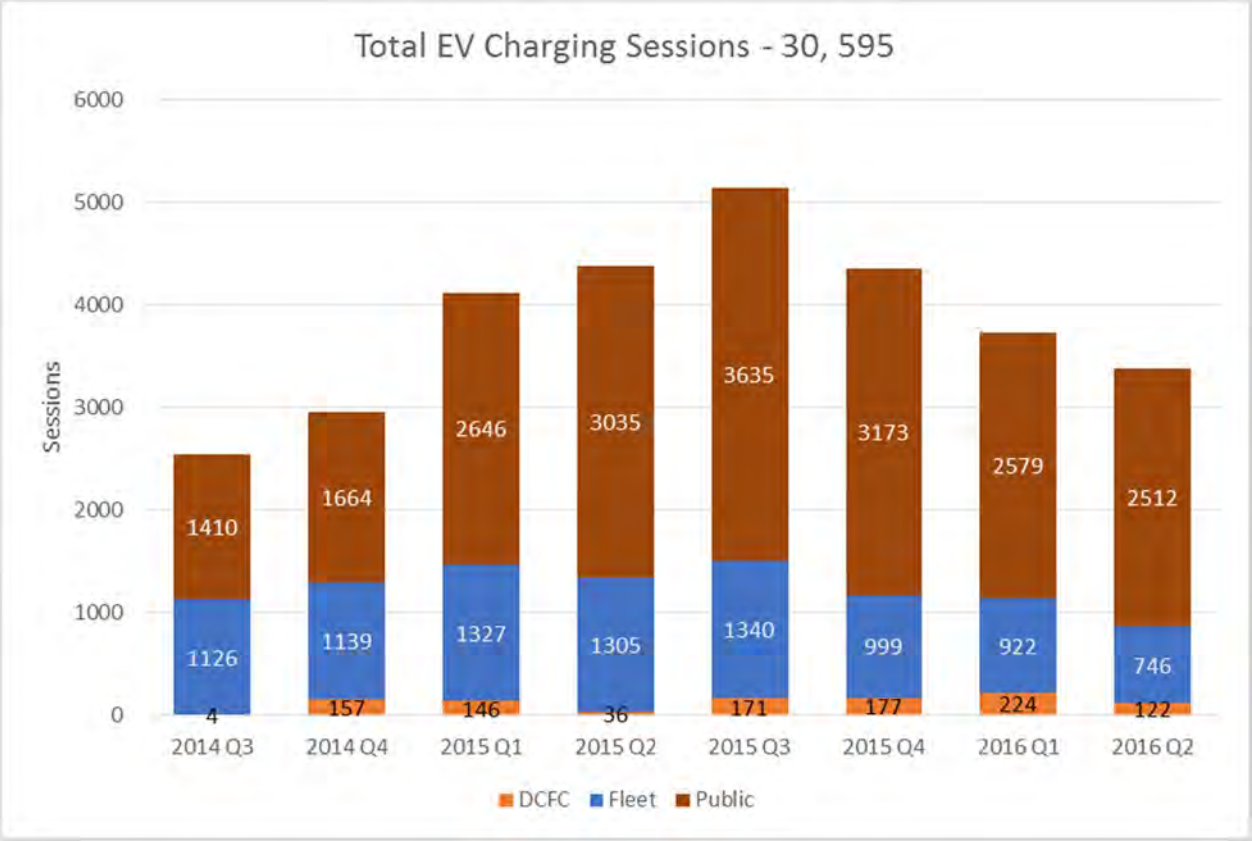
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Current Active Charging Stations – 137 Plug Points

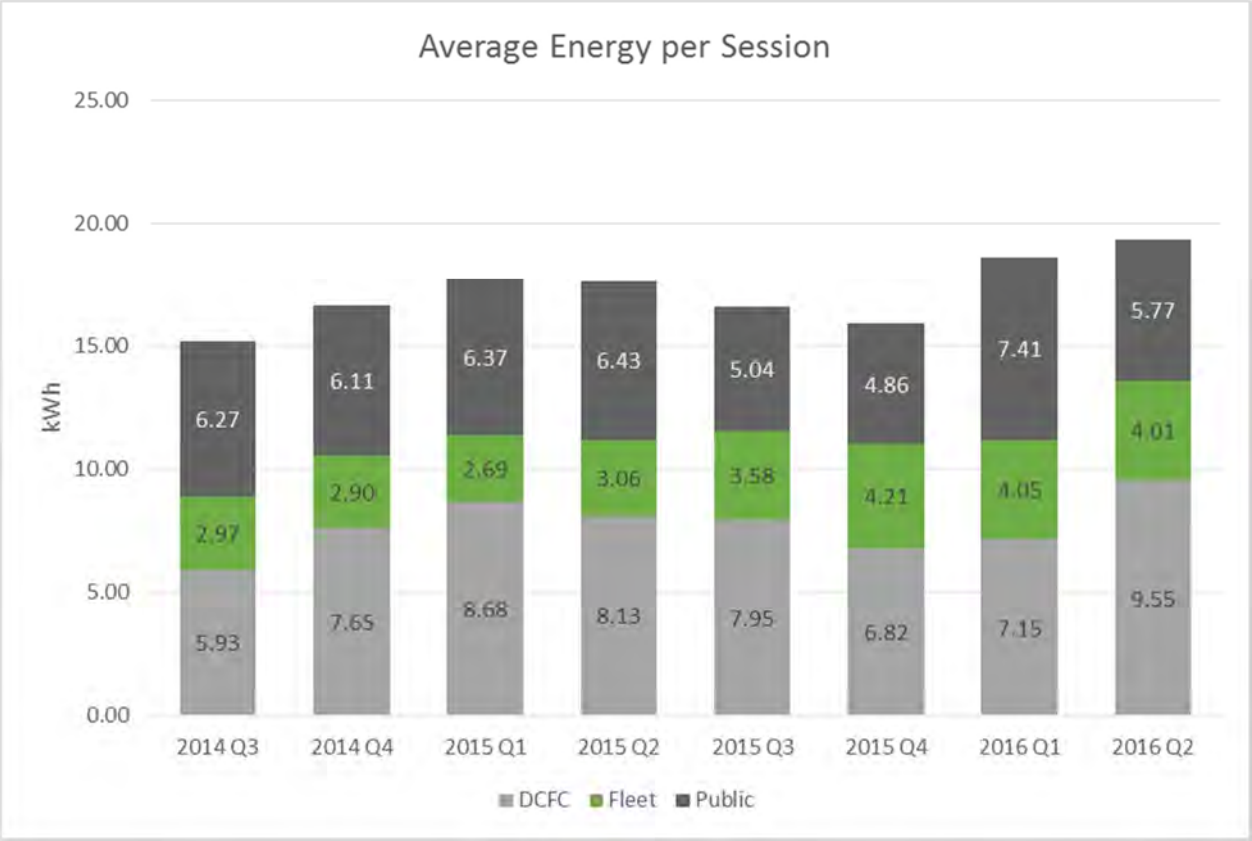
UCLA EV Activbe Charging Station Status				As of 06/30/2016
Location	Voltage	Connector type	Plug Points	Network/Status
LADWP JFB Lot 6 Level 2	110 V	NEMA 5-15	4	3G
PS 9 Level 4	110 V	NEMA 5-15	4	V2G testing
PS 9 Level 6	110 V	NEMA 5-15	4	WiFi,
PS 8 level 2 North	110 V	NEMA 5-15	4	3G
PS 8 level 2 South	208 V	J1772	4	3G
PS 8 level 2 North	208 V	J1772	4	3G
PS 2 level 2	110 V	NEMA 5-15	4	3G
PS 3 level 4	110 V	NEMA 5-15	4	3G
PS 3 level 2	208V	J1772	4	3G
PS 4	208 V	J1772	8	wired
PS 2	208 V	J1772	4	3G
UCLA Medical Center	208 V	J1772	4	wired
Sunset Village Parking (fleet)	110 V	NEMA 5-15	84	wired and Wif
Nissan Level 3 Charger (PS 4)	480 VAC	CHAdeMO	1	wired and Wif

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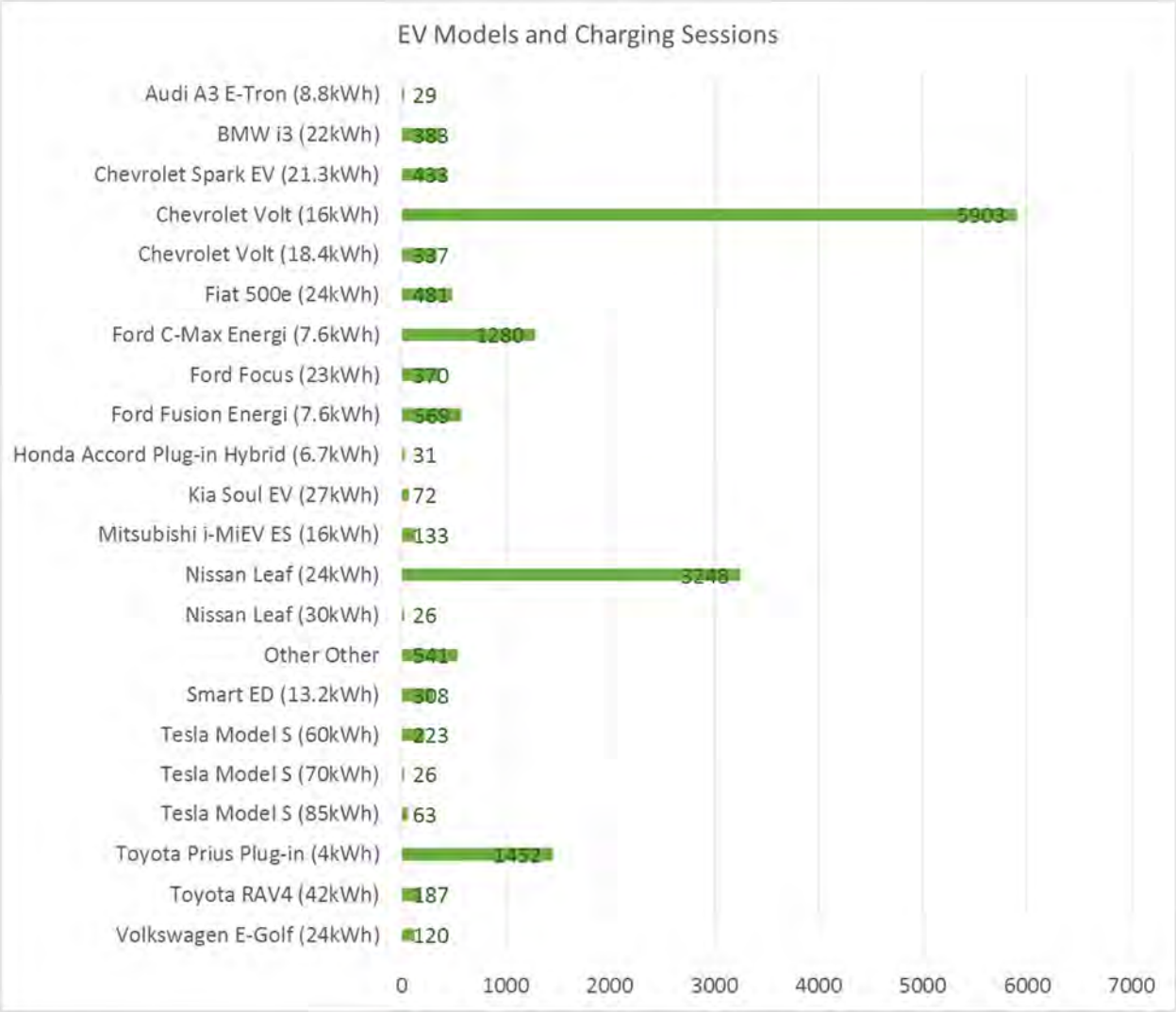


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Note: The lack of DCFC data is due to the LADWP flooding issues on UCLA parking structure # 4 on July 29, 2014. The DCFC was turned off after the flood due to safety concern and was turned back on September 23, 2014.

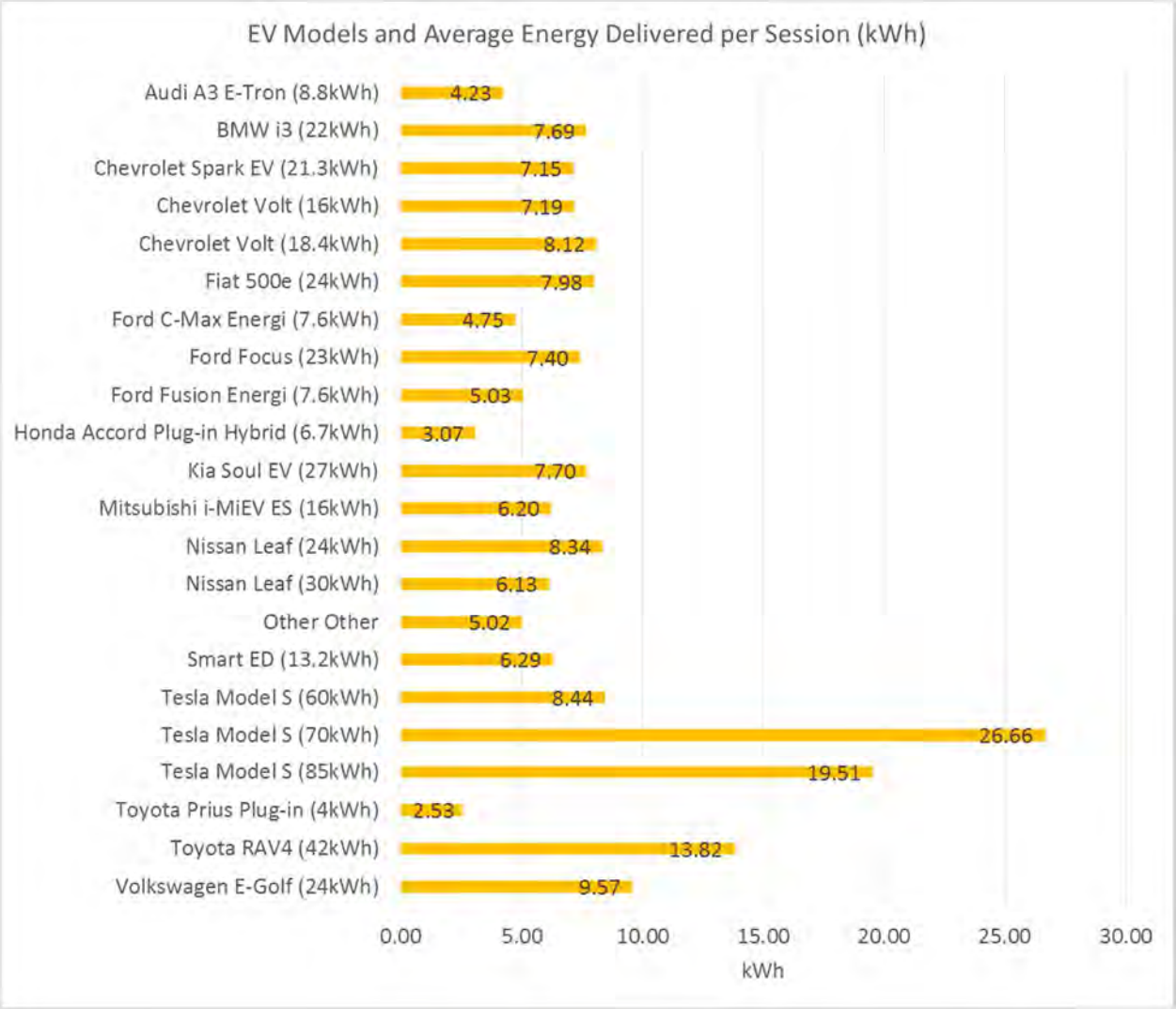
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Note:

1. Data Based on work place (public) charging only – excluding fleet vehicles.
2. "Other Other" indicates that users do not wish to reveal his/her vehicle model.

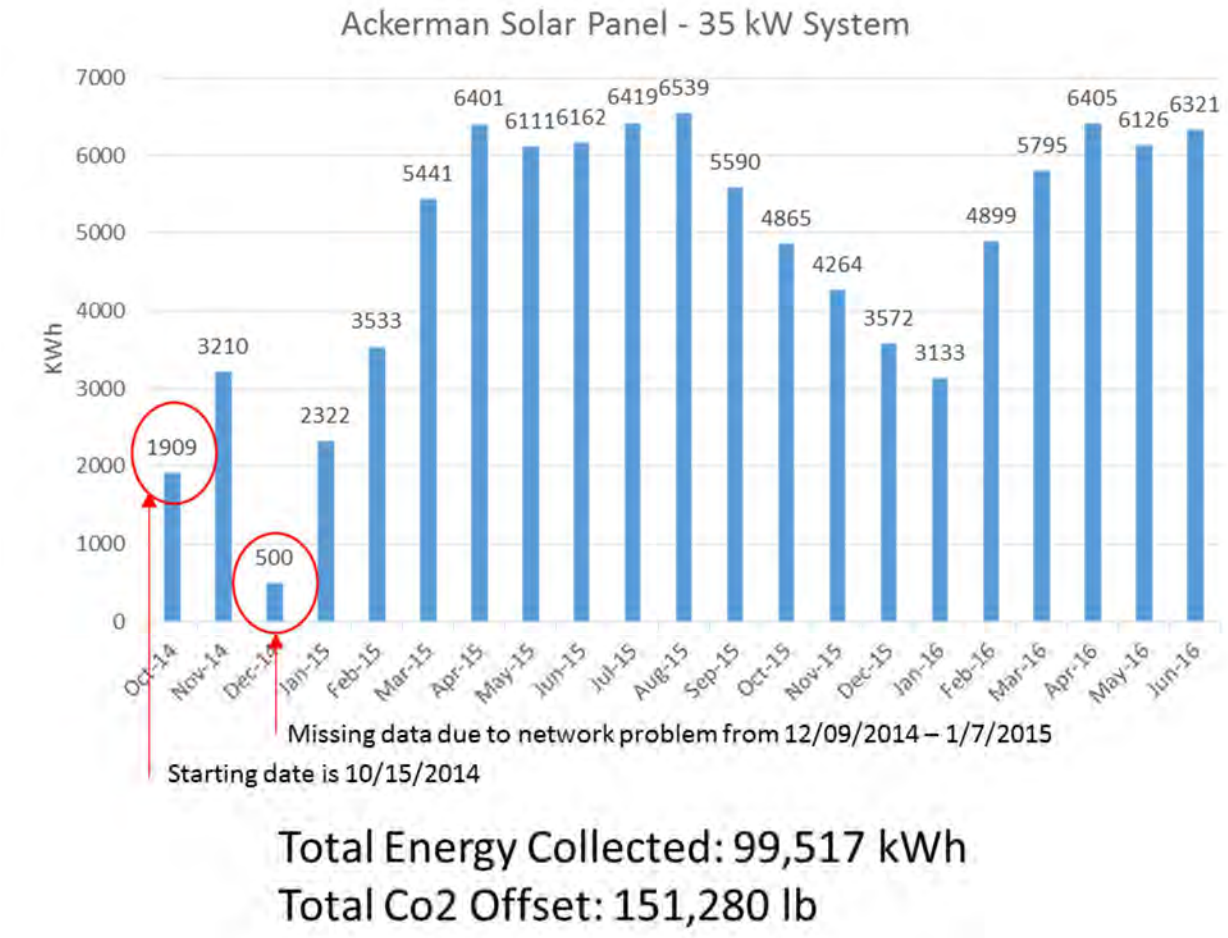
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Note:

1. Data Based on work place (public) charging only – excluding fleet vehicles.
2. "Other Other" indicates that users do not wish to reveal his/her vehicle model.

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1.2. SMERC Technologies used in each Use Case

In Table 1, a list of UCLA's EV project's Use Case is listed. The corresponding technologies used to accomplish each Use Case are identified. Table 2 shows a comparison of actual accomplishments with the goals and objectives.

Table 1. SMERC Technologies v.s. Use Case

No.	Use Case	WINSmartEV™	SMERC V2G	SMERC BESS	SMERC SCC
1	EV.01 – Monitor all chargers	X			
2	EV.02 – Reading Power consumption	X			
3	EV.03 – Control of chargers	X			
4	EV.04 – Disconnect a charging vehicle	X			
5	EV.05 – Smart charging through mobile interface	X			
6	EV.06 – Use of battery into grid G2V	X			X

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7	EV.07 – Use of Battery into Grid – G2V & V2G	X	X		
8	EV.09 – Inductive charging (report only)				
9	EV.10 – Various vehicle charging	X			
10	EV.12 – Local grid balancing and management	X		X	X
11	EV.13 – Community storage on EV battery and external storage	X		X	
12	EV.16 – Aggregation of batteries	X			X
13	EV.17 – Integration of EV and Solar	X		X	X

Table 2. Comparison of actual accomplishments with the goals and objectives

No.	Use Case	Goals and Objectives	Actual Accomplishments
1	EV.01 – Monitor all chargers	All Charging Stations within Use Case scenario must report status to Control Center	Requirements accomplished.
2	EV.02 – Reading Power consumption	All Charging Stations within Use Case scenario must report status to Control Center	Requirements accomplished.
3	EV.03 – Control of chargers	All Charging Stations within Use Case scenario must report status to Control Center. Control Center will automatically manage the on/off state and the charging current of the charger(s) based on various conditions collected from the system and Mobile App.	Requirements accomplished. Status of Charge is available only on Chevy Volt and Nissan Leaf.
4	EV.04 – Disconnect a charging vehicle	All Charging Stations within Use Case scenario must report status to Control Center and the Control Center can send commands to terminal a charging session based on scheduling algorithm.	Requirements accomplished.
5	EV.05 – Smart charging through mobile interface	Mobile app is capable of locating charging stations and controlling EV charging based on programmable user preferences	Requirements accomplished.
6	EV.06 – Use of battery into grid G2V	To be able to collect aggregated EV power consumption and observe the EV charging Load peak demand for the purpose of potential demand response program	Requirements accomplished.
7	EV.07 – Use of Battery into Grid – G2V & V2G	Control Center successfully manage charging/discharging section based on time-of-use price in an automated manage; User successfully manage charging/discharging manually	Requirements accomplished.
9	EV.10 – Various vehicle charging	All Charging Stations within Use Case scenario must report status and consumption to Control	Requirements accomplished.

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		Center. Control Center will automatically manage the on/off state and the charging current of the charger(s).	
10	EV.12 – Local grid balancing and management	All Charging Stations within Use Case scenario must report status and consumption to Control Center and subsequently to Super Control Center. Participating EV charger must reduce charging current or turned off during a load shedding event.	Requirements accomplished.
11	EV.13 – Community storage on EV battery and external storage	All CES devices & Charging Stations within Use Case scenario must report status and consumption to Control Center.	Requirements accomplished. Battery system and EV are not physically on the same circuit.
12	EV.16 – Aggregation of batteries	All Charging Stations within Use Case scenario must report status and consumption to Control Center. Load Shedding can be successfully completed during demand response events.	Requirements accomplished.
13	EV.17 – Integration of EV and Solar	All Charging Stations, Batteries, and PV Panels within Use Case scenario must report status and consumption to Control Center	Requirements accomplished. PV and EV are not physically on the same circuit.

This report is focus on the result obtained from the following demonstrations:

- EV.01 – Monitor all chargers
- EV.02 – Reading Power consumption
- EV.03 – Control of chargers
- EV.04 – Disconnect a charging vehicle
- EV.05 – Smart charging through mobile interface
- EV.10 – Various vehicle charging

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1.3. Cost, Benefits and Lessons learned (WINSmartEV™ and WINSmartGrid™)

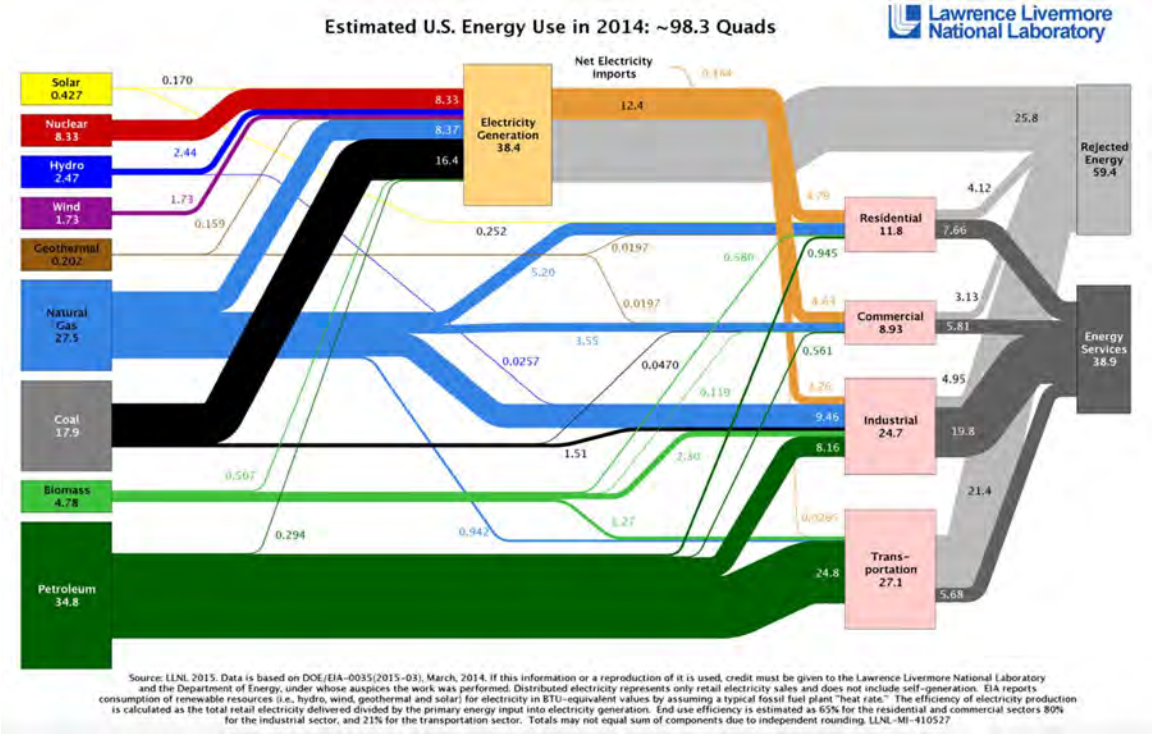
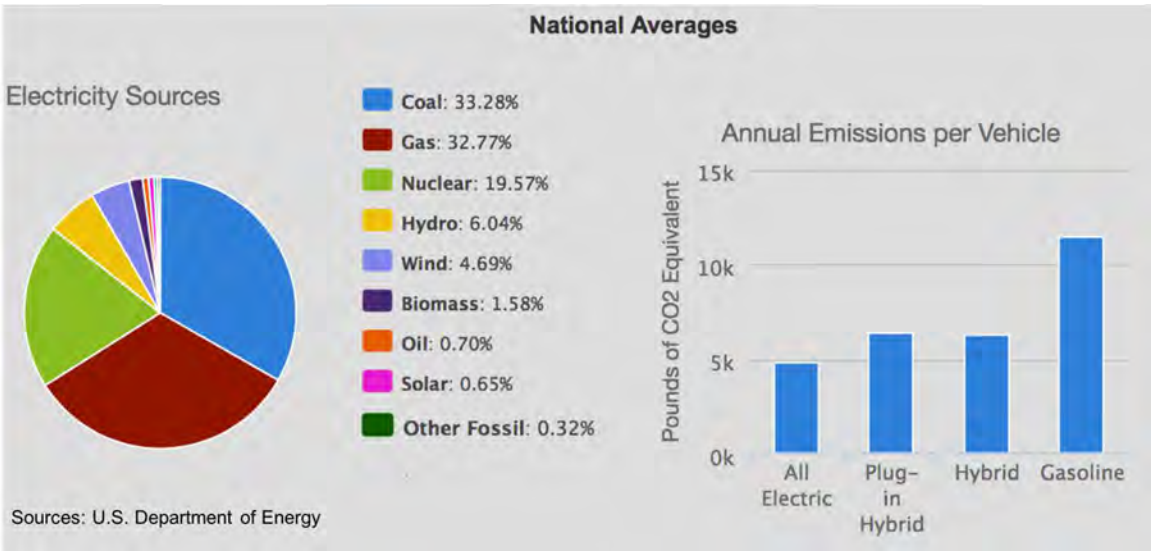


Figure 1 Estimated U.S Energy Use in 2014

Figure 1 shows that the ejected energy from transportation is nearly 4 times to energy services. This is due to low energy efficiency of combustion engine. Modern gasoline engine efficiency is around 25%-30% when used to power a car [1]. For electric vehicles, on the other hand, they convert 59%-62% of the electrical energy from the grid to power at the wheels [2]. Since EVs emit no tailpipe pollutants, it is much more environmentally-friendly than conventional gasoline car.



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Figure 2 National average: electricity sources and annual vehicle emission comparison

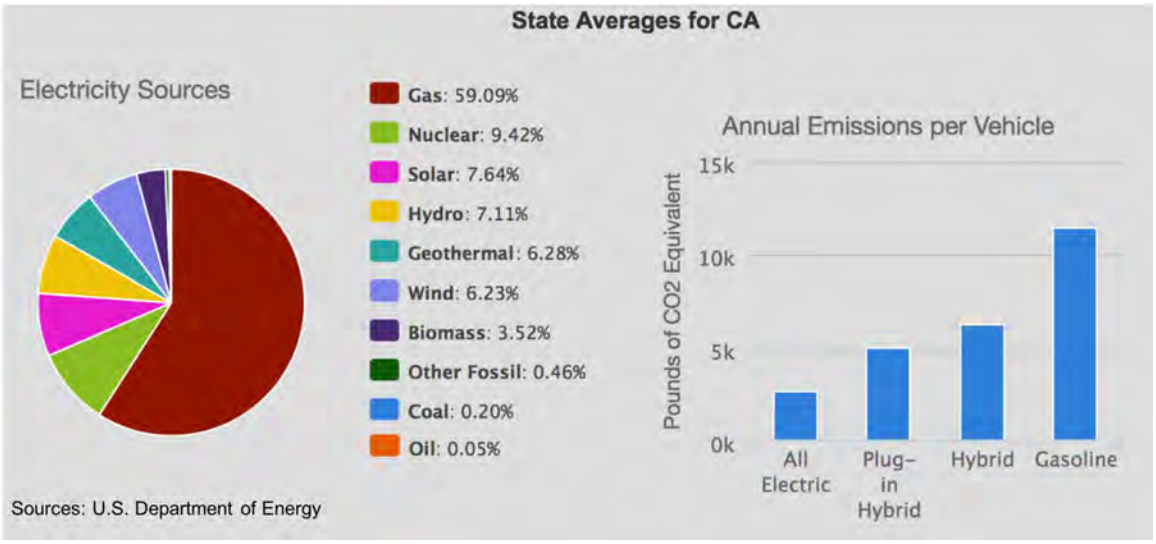


Figure 3 State average for CA: electricity sources and annual vehicle emission comparison

The Figure 2 and Figure 3 [3] show the electricity usage and annual vehicle emission comparison. The emission of electric vehicles is the lowest and the gasoline cars. Although electricity vehicles have zero tailpipe emission, emission may still be produced by the source of electricity generation. Thus, the source of the electricity generation is the key factor to evaluate EV emission. The average EV emission in California is lower than national average because more renewable energy used.

The smart EV charging system, i.e., WINSmartGrid™ and WINSmartEV™, have brought tremendous benefits to the overall system performance, in terms of cost, peak demand reduction and the energy efficiency. Power consumption from EVs is usually larger than other home appliances, such as lighting bulb, microwave, etc. Concurrent charging behaviors from multiple EV charging drivers under the same substation will create unexpected high load in the very short time period, which degrades the power quality and makes the whole system not reliable. Traditionally, user charging behaviors from EV users are stochastic process, which is difficult to develop a comprehensive predictive model to make accurate estimations for all users. Thus, the original system demand and cost have not been optimized, without considering the aforementioned factors.

Within the proposed systems, EV energy scheduling service, with smart charging scheduling algorithms are developed to achieve better system cost performance, meanwhile satisfying the energy demand and preferences from EV drivers. The on-line program will examine the real-time energy demand requests from users at each EVSE and perform the schedule optimization to deliver enough energy to each of the connected vehicles and maintain the enough energy delivery. According to the real-time energy prices, the EV charging load has been shifted to time windows with lower energy prices and total system demand, thus, reducing the total system peak load (For details, please price-based scheduling algorithms in section 2.5.4 and Event-based Smart Charging Algorithm in section 2.5.7). Meanwhile, the engaged EV drivers have the flexibility to select different energy rates they accept and input their own travel schedules to minimize the charging cost. To minimize load variance, we also developed a charging algorithm

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considering of user behavior uncertainties in Section 2.5.8. IEC 61850 protocol is used to increase system interoperation for different technology platforms. Based on the simulation from real-world EV usage data, the total energy cost saving can be achieved by selecting the energy rates and travel schedules wisely (Please see price-based algorithms for details in section 2.5.4). PV system has been integrated to support and offset EV charging, thus decreasing emission of EVs that charge in UCLA campus. The Battery Energy Storage System (BESS) also integrated in the system to provide greater flexibility to accommodating new energy technologies, renewable, intermittent and distributed sources.

Considering the reduced consumption of fossil fuels and green house gas(GHG) emissions, the system developed and implemented by UCLA Smart Grid Energy Research Center(SMERC) has brought the following contributions to the public:

- Lower costs –significantly reduce the costs for both customers and utilities, by optimizing numerous EV loads under various pricing strategies
- Greater reliability –improve system reliability by optimizing the aggregated load considering the supply and renewably generated electricity, while preventing system level failures and guaranteeing energy delivery.
- Environmental benefits – through facilitation of renewable energy resource integration, the risk that catastrophic global warming that will take place will be reduced, thereby preventing further extreme environmental consequences such as species stresses and extinctions, global sea-level rise, and other undesirable penalties of continued burning of fossil fuel.
- Public health – Reducing harmful emissions from fossil fuel burning electricity generation plants and providing renewably generated electricity to replace emissions from fossil fuel burning vehicles is anticipated to greatly reduce asthma rates and severity of asthma attacks, as well as the risk of catastrophic global warming that causes peak intensity and/or record-breaking severity of extreme weather events with their well-known cost to human life and health.
- Consumer appeal –herein will have great customer appeal, as it will help to reduce electricity bills by offering user-friendly energy management portals on various platforms, making it convenient to setup and monitor energy consumption.
- Energy security –help integration of distributed renewable energy resources, allowing local communities, regional governments, and nations to achieve highly sought energy independence, which equals energy security in public policy circles.

2. Use Cases and Demonstrations

This section provides a high level description of each Use Case, identifies the main functions and data collection of each Use Cases. The common infrastructure configuration (hardware/software), prototypical as well as production system design/development and research works are included at later sections.

2.1.1. Use Case EV.1 Monitoring All Chargers

Description: Display the status of all chargers and indicate whether or not the charger is charging.

Main Functions in this Use Case/Demonstration:

1. **Real time charger status monitoring** – Control center sends charger request of current status, the charger respond with Station Name, Time stamp, voltage, current, frequency, power factor, active

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power, apparent power and main energy. This data is store in the database and displayed on the control center to show real time status. A sample charger status dashboard view is show below:



PS8, 555 Westwood Plaza, Los Angeles, CA90095

Charging Box Name	Charging Algorithm	Level	Network Type
PS8L201LI	Price Bid L1	1	3G/4G+WiFi
PS8L202LII	Energy Sharing L2 S	2	3G/4G
PS8L203LII	Energy Sharing L2 S	2	3G/4G

Charging Stations

Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	Timestamp	Voltage	Current	Active Power	Energy Consumed
PS8L201LIA1	Standby	Offline	-	-	1	-		09/30/2014 11:01:31	0.00V	0.00A	0.00W	198.638kWh
PS8L201LIA2	Standby	Offline	-	-	2	-		09/30/2014 11:01:31	0.00V	0.00A	0.00W	8.161kWh
PS8L201LIA3	Standby	Offline	-	-	3	-		09/30/2014 11:01:31	0.00V	0.00A	0.00W	44.726kWh
PS8L201LIA4	Standby	Offline	-	-	4	-		09/30/2014 11:01:31	0.00V	0.00A	0.00W	439.592kWh

Charging Stations

Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	Timestamp	Voltage	Current	Active Power	Energy Consumed
PS8L202LIIA0	Standby	Offline	-	0%	1	-		09/30/2014 11:04:07	0.00V	0.00A	0.00W	3541.770kWh
PS8L202LIIA1	Standby	Offline	-	0%	2	-		09/30/2014 11:04:07	0.00V	0.00A	0.00W	3468.137kWh
PS8L202LIIA2	Standby	Offline	-	0%	3	-		09/30/2014 11:04:07	0.00V	0.00A	0.00W	3554.133kWh

Charging Stations

Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	Timestamp	Voltage	Current	Active Power	Energy Consumed
PS8L203LIIA1	Standby	Offline	-	0%	1	-		09/30/2014 11:00:15	0.00V	0.00A	0.00W	0.000kWh
PS8L203LIIA2	Standby	Offline	-	0%	2	-		09/30/2014 11:00:15	0.00V	0.00A	0.00W	0.000kWh
PS8L203LIIA3	Standby	Offline	-	0%	3	-		09/30/2014 11:00:15	0.00V	0.00A	0.00W	0.000kWh
PS8L203LIIA4	Standby	Offline	-	0%	4	-		09/30/2014 11:00:15	0.00V	0.00A	0.00W	0.000kWh

PS9, 675 Charles E. Young Dr, Los Angeles, CA90095

Charging Box Name	Charging Algorithm	Level	Network Type
PS9L401LI	Price Bid L1	1	WiFi+PLC
PS9L601LI	Price Bid L1	1	WiFi

Charging Stations

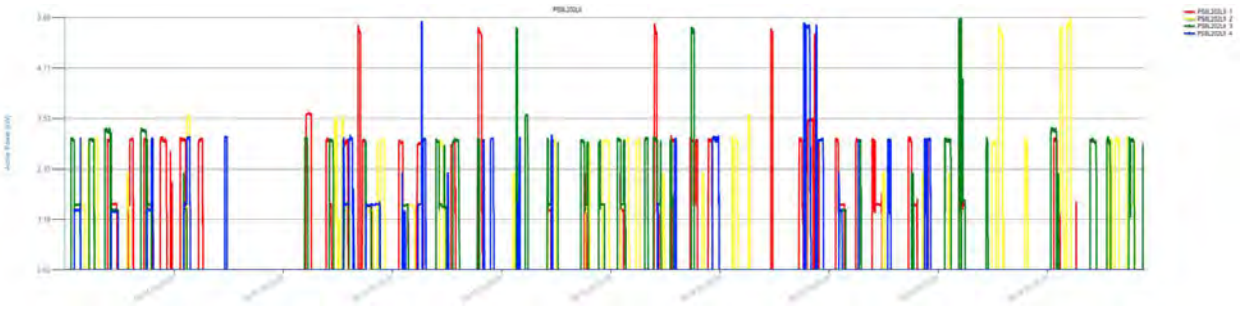
Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	Timestamp	Voltage	Current	Active Power	Energy Consumed
PS9L401LIA1	Standby	Off	-	-	1		Nissan Leaf	09/30/2014 11:03:11	115.54V	0.00A	0.00W	2657.328kWh
PS9L401LIA2	Standby	Off	-	-	2			09/30/2014 11:03:11	115.58V	0.00A	0.00W	718.195kWh
PS9L401LIA3	Charging	On	-	-	3		Nissan Leaf	09/30/2014 11:03:11	115.63V	11.72A	1348.96W	374.900kWh
PS9L401LIA4	Standby	Off	-	-	4			09/30/2014 11:03:11	115.66V	0.00A	0.00W	271.998kWh

Charging Stations

Control	Charging Status	Station Status	Plugged-in	Duty Cycle	Station	Current User	EV Information	Timestamp	Voltage	Current	Active Power	Energy Consum
PS9L601LIA1	Standby	Off	-	-	1		Toyota Prius Plug-in	09/30/2014 11:04:47	110.65V	0.00A	0.00W	693.190k
PS9L601LIA2	Charging	On	-	-	2		Toyota Prius Plug-in	09/30/2014 11:04:47	110.77V	11.70A	1294.55W	442.710k

Sample Dashboard View of Real time Charger status

2. **Historical data storage and analysis**: The control center can retrieve historical data and plug charts for analysis. Sample of station record chart is shown below:

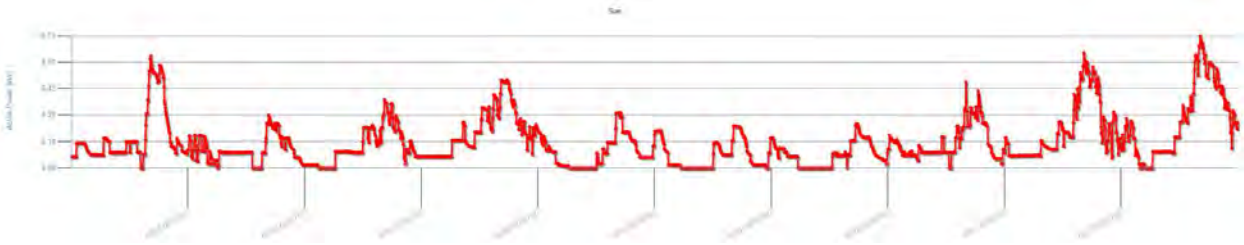


Sample station record chart for PS 8 box #3 in 2015-09



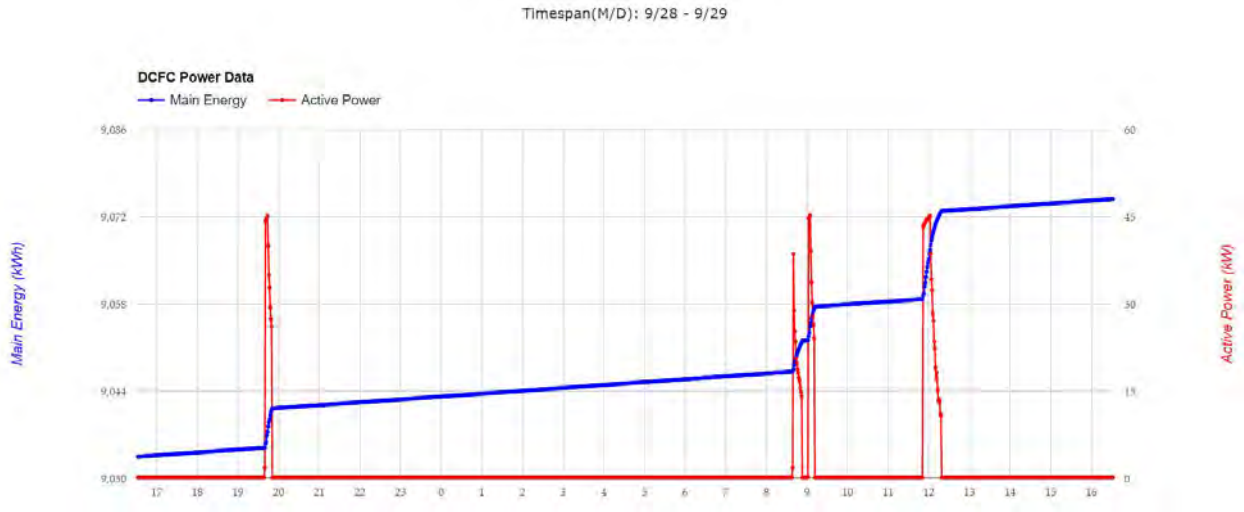
Sample total activate power in **UCLA** level 1 and level 2 Charger (9/1/2015 – 9/10/2015)

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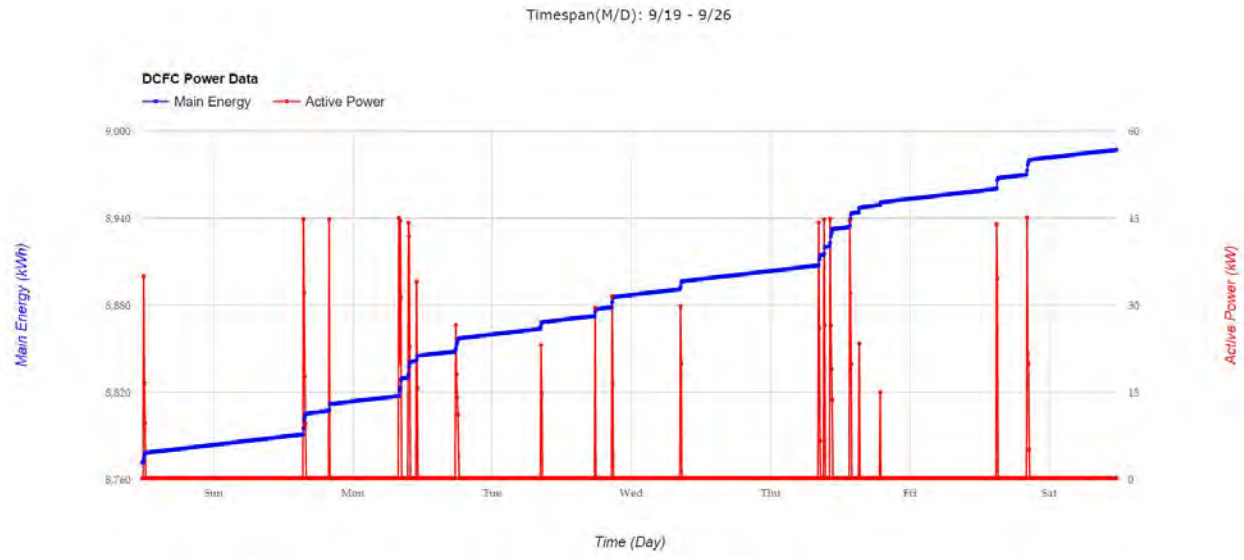


Sample total active power in **Sunset Village fleet** charger (9/1/2015 – 9/10/2015)

3. **DCFC real time and historical data analysis:** The control center periodically (1 min) receive data from the meter at the DCFC and store them in database. The following figures show samples of DCFC's real time and historical data.



Sample Power and Energy reading on 9/28/2015 and 9/29/2015



Sample Power and Energy reading on 9/19/2015 and 9/26/2015

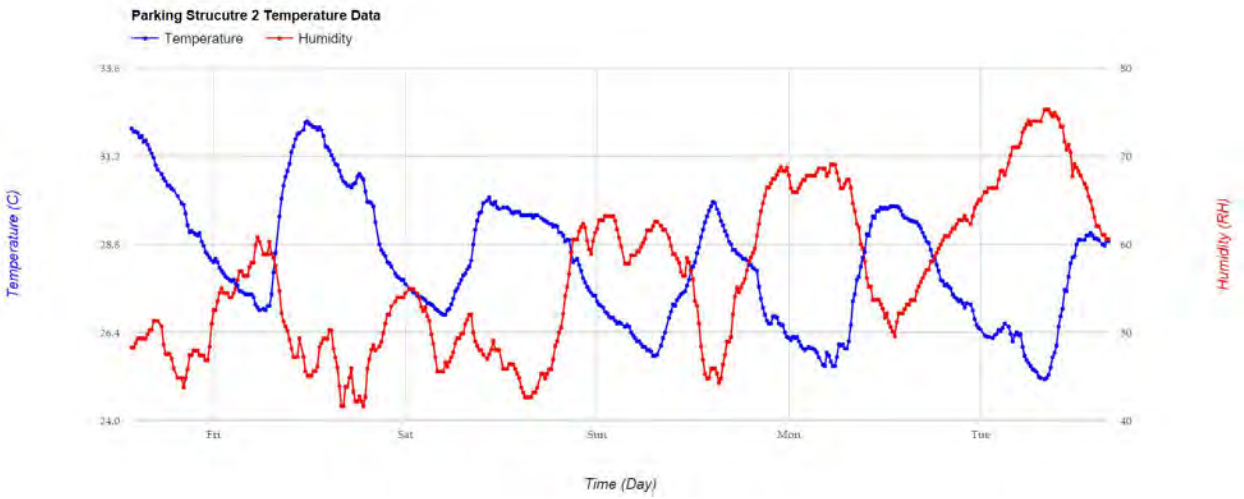
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2.1.2. Use Case EV.2 reading power consumption for vehicles connected to chargers

Description: Monitor and store power consumption information for charging station. Real time and historical data will be collected and stored at the control centers.

Main Functions in this Use Case/Demonstration:

1. **Real time charger status monitoring** – Control center sends charger request of current status, the charger respond with Station Name, Time stamp, voltage, current, frequency, power factor, active power, apparent power and main energy. This data is store in the database and displayed on the control center to show real time status. A sample charger status dashboard view is show in Use Case EV.1.
2. **Historical data storage and analysis**: The control center can retrieve historical data and plug charts for analysis. A sample of station record chart is shown in Use Case EV.1.
3. **DCFC real time and historical data analysis:** The control center periodically (1 min) receive data from the meter at the DCFC and store them in database. A sample DCFC's real time and historical data dashboard view is shown in Use Case EV.1.
4. **Recording of Ambient Temperature and humidity –** The ambient temperature and humidity at various parking lots are reported back to the control center through temperature and humidity sensors as part of the scenario data. A sample temperature and humidity data recording is show in the figure below:

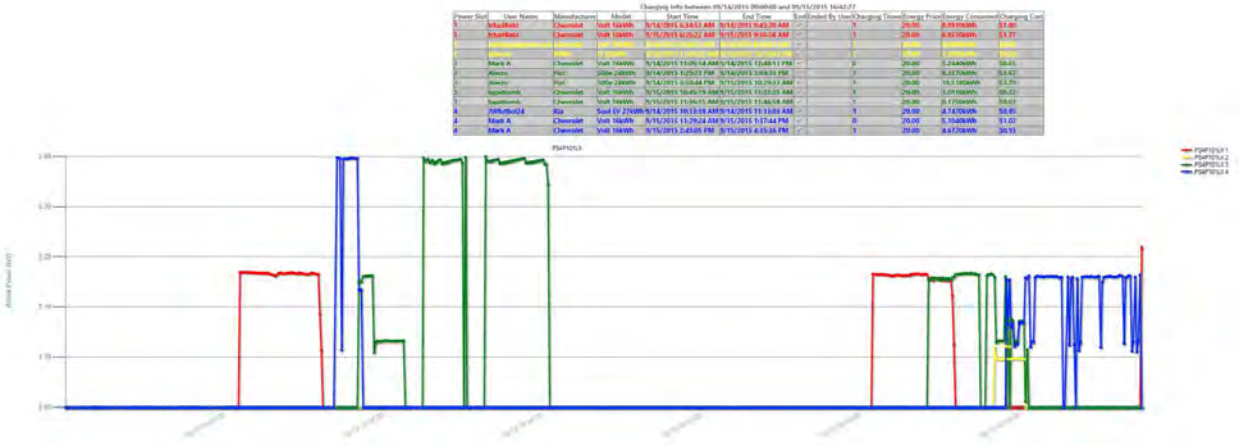


Sample temperature and humidity chart in PS 2

5. **Recording of Status of Charge (SOC) and Remaining Mileage:** The SOC data was collected only on the project Vehicle Nissan Leaf. The SOC data is recorded every 5 min when the SOC monitoring modules is plugged and the vehicle is powered on. The remaining mileage is recorded based on user's input when they activate their charging session.
6. **Recording of Charging Records at starting and ending of a charging session:** The Control center sends requests to EV chargers and records station name, EV model, starting/ending time stamp, starting/ending voltage, starting/ending current, starting/ending power factor, starting/ending

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active power, staring/ending apparent power, starting/ending main energy, and starting remaining mileage. A sample of charging session listed in tabular format is shown in the figure below:



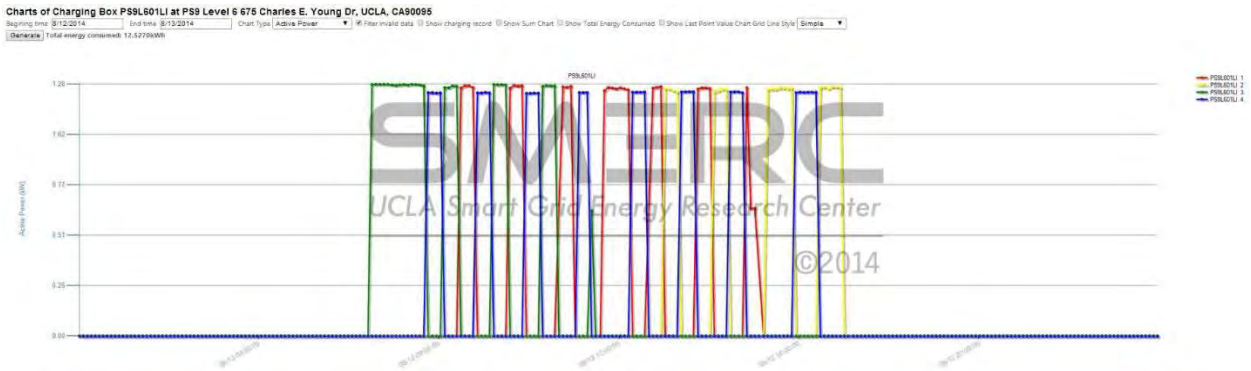
Charging record Sample on 9/14/2015

2.1.3. Use Case EV.3 Control of Chargers

Description: Control Center will automatically manage the on/off state of the charger(s) based on various conditions collected from the system, charger, and EV.

Main Functions in this Use Case/Demonstration:

1. **Automatic on/off control and charging current management of EV chargers:** the control center can send commands to turn on/off an EV charger or to change the charging current of an EV charging station. Under normal operation, level 1 EV charger in UCLA turns on and off charging powers to each connected EV alternatively (one hour duration) to charge each vehicle (4 vehicles with one level 1 EV charger). A sample of this level 1 multiplexing function is show in the figure below:



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For level 2 chargers, under normal operation, the control center will automatically distribute the maximum available power among connected EVs in a charging box to allow 4 vehicles to charge simultaneously. The following figure shows a sample of level 2 EV charging with multiple vehicles and the level 2 EV charger.



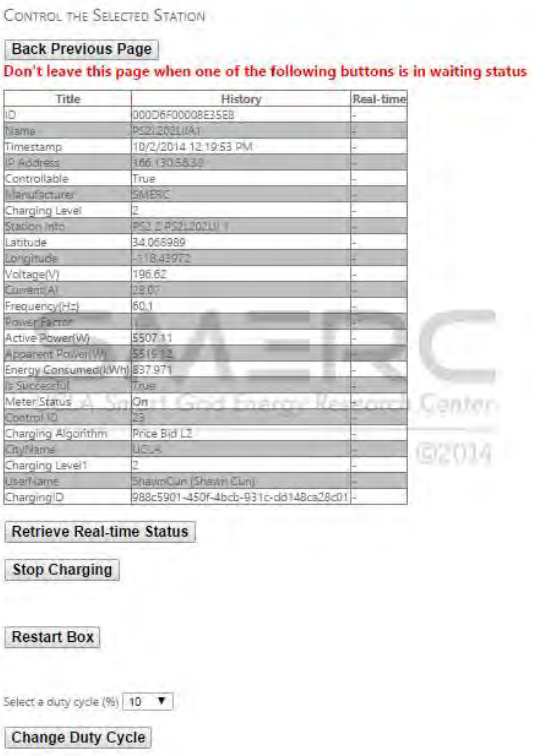
2.1.4. Use Case EV.4 Disconnect Vehicle that is charging

Description: Connect/disconnect commands will be sent from the central control centers to a specific charging station via addressable instructions.

Main Functions in this Use Case/Demonstration:

1. **Manual activate or de-activate an EV charger from control center:** the control center operator can manually send commands to turn on/off an EV charger or to change the charging current of an EV charging station. A sample manual activation and de-activation interface in the control center is shown in the figure below:

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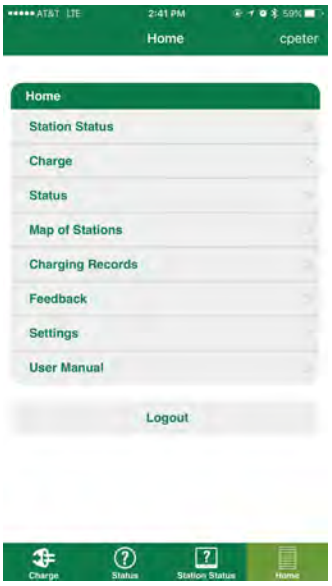
2.1.5. Use Case EV.5 Smart Charging through Mobile Interface

Description: Mobile devices (PDA, cell phone, & laptops) will be used to control EV battery charging and back fill operations.

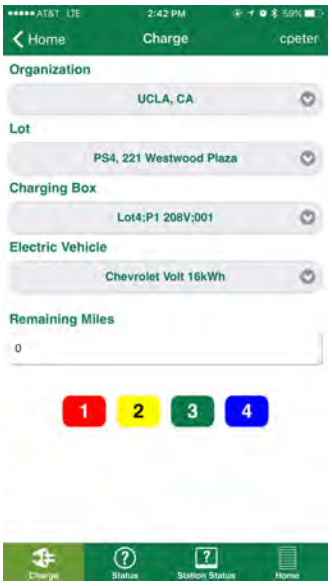
Main Functions in this Use Case/Demonstration:

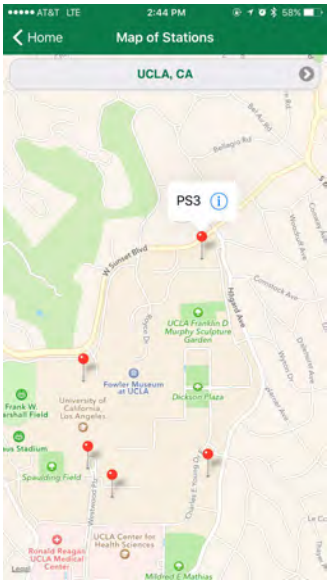
1. **EV drivers use Mobile Apps to identify available chargers, find direction to chargers, activate charger, monitor charging status, disconnect chargers and specify preference:** the mobile app developed under this project allows all the above operations and was distributed to the EV drivers in UCLA to interact with the EV chargers. Some sample screen shots of mobile app is included below:

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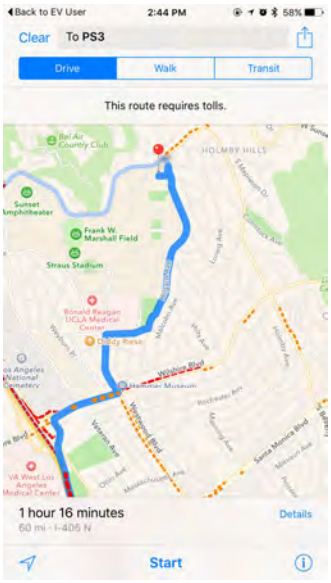












Your closed charging info

EV Station System <smercev@gmail.com> Wed, Oct 1, 2014 at 1:23 PM
To: chichengwi@gmail.com

Charging Box: Lot 9;Floor 6;120V;001 ; Station: 3
Address: 675 Charles E. Young Dr UCLA CA90095
Start time: 10/01/2014 13:22:36
Stop time: 10/01/2014 13:23:33
Charging times: 0
Energy consumed: 0.0000kWh
$Charging cost: $0.00
This charging is closed automatically by our system
Please do not reply to this message as all replies will automatically be discarded. If you have any questions about this charging record, contact SMERC, UCLA.
Thanks for using SMERC, UCLA EV Charging System

SMERC Smart Grid Energy Research Center ©2014

2. **EV Control Center to adopt various EV charging scheduling algorithms to turn EV charger on/off or to change charging current:** based on available scheduling algorithm, the EV Control Center

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can turn EV charger on/off or change charging current based on the scheduling algorithm. Currently, UCLA SMERC has tested the following scheduling algorithms:

a. Normal operation:
    i. Level 1: Equal time sharing algorithm (one hour multiplexing among 4 power outlets.)
    ii. Level 2: Equal current sharing algorithm among all connected EVs in a EV charging box (current shared by 4 vehicles)
b. Demand response event:
    i. The control center provide OpenADR 2.0 interface to curtail EV charging load in a demand response event. The control center will send commands to selected (or pre-selected) EV chargers to cut the charging current to minimum (level 2) or to turn off the chargers (level 1). During demand response event, new charging session are not allowed to start the charging.
c. Price-bidding algorithm: The user will specify their acceptable energy price on the mobile app when they start a charging session. The vehicle will only be charged only when the energy price is below the specified value.
d. Priority Charging: The control center may assign the users with a priority number (1-10), the charging time (level 1) or charging current (level 2) are distributed to the vehicles based on the priority number.
e. Remaining Mileage based priority charging: vehicles with lower remaining mileage are given higher priority to charge.
f. PQA based load curtailment: the control center will send commands to EV charger to cut the charging current to minimum (level 2) or to turn off the chargers (level 1) when the power quality of a parking structure is degrading.
g. Temperature based load curtailment: due to high temperature challenges on the EV controller and microprocessor, this new algorithm will be developed and tested. When the ambient temperature at a parking structure is higher than a threshold value, the charging current will be reduced to accommodate overheating problem inside the EV charger.

2.1.6. Use Case EV.10 Various Vehicle Charging

This is a newly assigned task. Please see current report based on prior observation and partial data collection in section 5.

Description: Monitor and compare the charging of various makes of vehicles available to the project.

Main Functions in this Use Case/Demonstration:

1. **Recording of Charging Records at starting and ending of a charging session:** The Control center sends requests to EV chargers and records station name, EV model, starting/ending time stamp, starting/ending voltage, starting/ending current, starting/ending power factor, starting/ending active power, staring/ending apparent power, starting/ending main energy, and starting remaining mileage. A sample of charging session listed in tabular format is shown in the figure below:
2. **Testing and recording Energy efficient on project vehicles:** under this project, UCLA SMERC will continue to test the charging behaviors, performance and energy efficiency of the following project vehicles:

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a. Tesla Model S 60 kWh
b. Nissan Leaf 24 kWh
c. Chevy Volt 16 kWh
d. Ford Focus 23 kWh
e. Mitsubishi i-MiEV 16 kWh

3. WINSmartEV™ Smart Charging Infrastructure

WINSmartEV™ is a system that is focus on the integration of electric vehicles into the power grid application. As shown in Figure 1, at the communication layer, it utilizes various wireless communication protocols to collect data such as Vehicle ID, power usage in kW, voltage and amperage and to send control signals to connect and disconnect charger based on various input from grid capacity, user preference time of use, and demand respond events. It also provides a user interface to allow mobile devices to monitor and control electric vehicle's charging schema. The expert system determines the optimized charging and backfill operations based on various inputs from EV profile, user preference, demand respond event, grid capacities.



Figure 4. WINSmartEV™ Components Architecture

The characteristics of this system are: 1) Low Power technology, 2) Standards-based hardware adapted to fit the problem resulting in lower overall cost, 3) Wireless infrastructure for monitor and control, 3) Service architecture with three layers – Edgeware, Middleware and Centralware, 4) Open architecture for easy

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integration, 5) Plug-and-Play approach to the network installation, 6) Reconfigurability – The capability of the technology to be reconfigurable allows OTA (over the air) upgrade of the firmware to be able to handle different and devices, applications, sensors, controllers, thermostats, etc.

A high level of communication architecture is shown in Figure 2. In this demonstration, UCLA team has experimented with various communication protocols and determine the optimized communication architecture to connect various components.

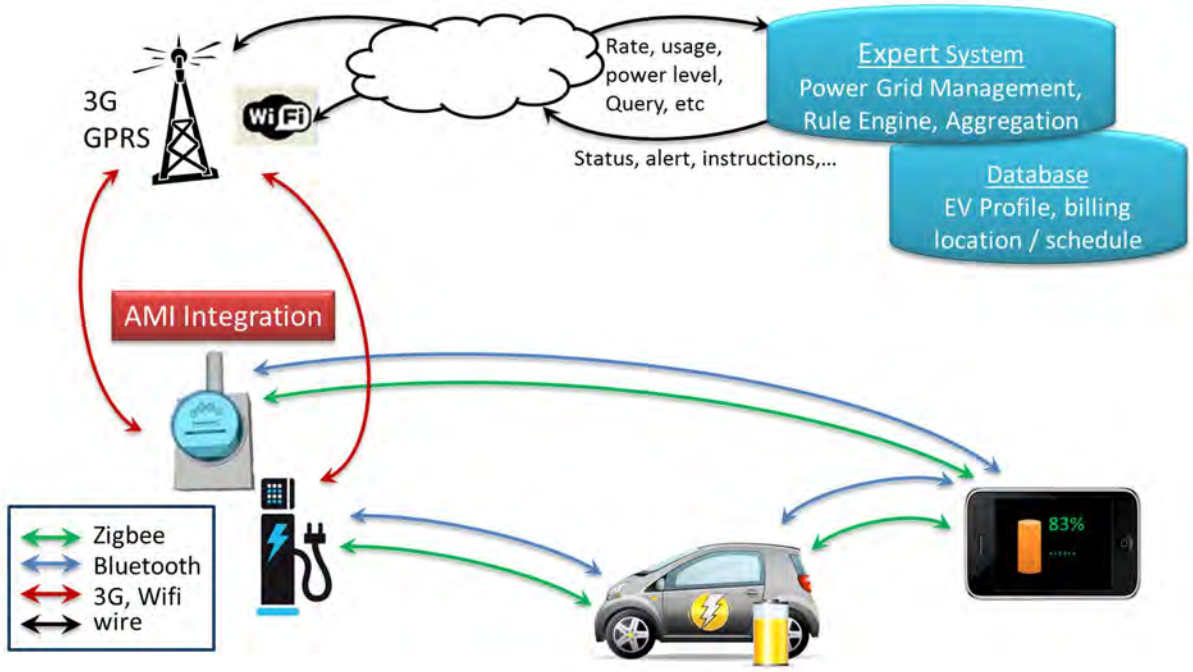


Figure 5. WINSmartEV™ Network communication

The UCLA Smart Grid Energy Research Center (SMERC) has dedicated its efforts on large-scale testing of its smart charging network WINSmartEV™ using UCLA parking structures as the test bed. We have tested various communication networks and designed an optimal communication architecture based on the specific characteristics of the parking structures.

The WINSmartEV™ EV charging network utilizes a centralized control system to monitor and regulate the network for real-time smart charging services. This smart charging infrastructure uses standard networking technologies to create a network that facilitates charging services for the end user and monitoring and control tasks for maintainers/operators. The charging services are completely adaptable by way of local or remote charging algorithms. In addition, the architecture incorporates multiplexing capabilities with a unique safety system that integrates safety on all levels of control.

With results obtained from this project, the topology of the EV network's architecture was created as shown in Figure 6.

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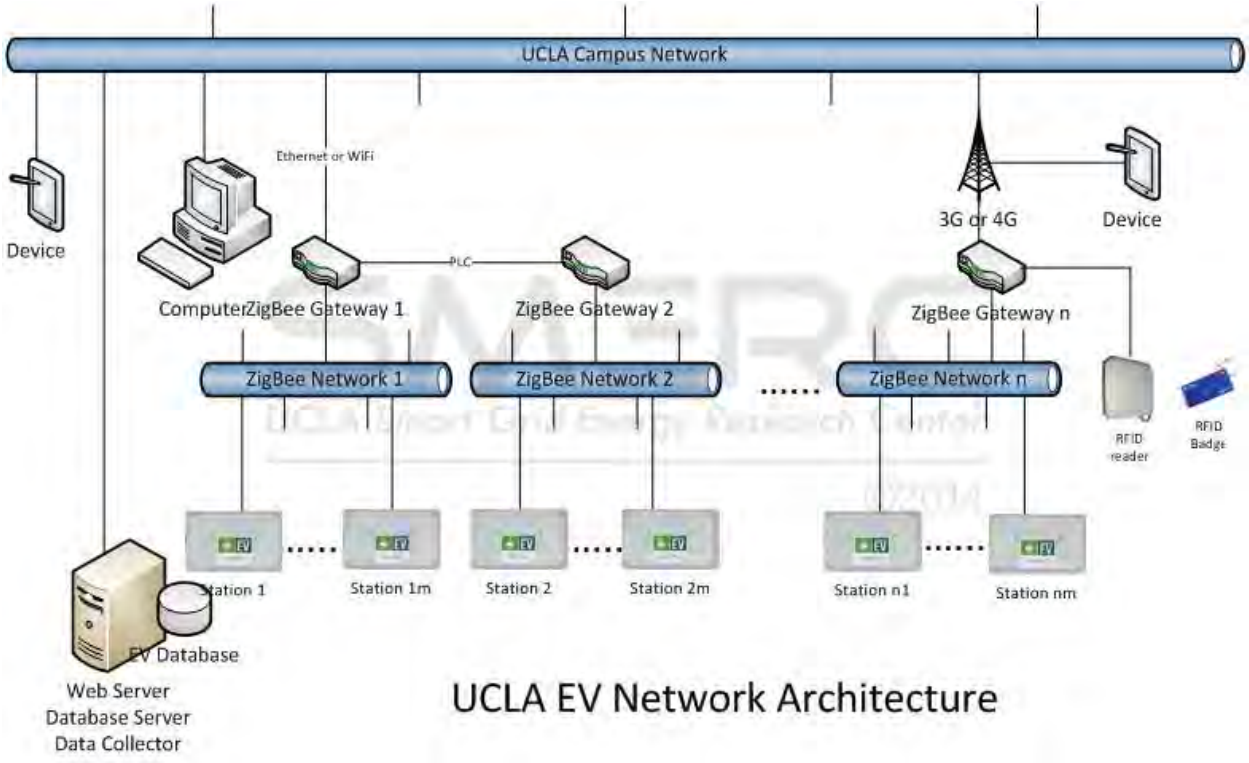


Figure 6. Topology of WINSmartEV™

As shown in Figure 6, built under UCLA campus network, the EV communication network utilizes campus Ethernet, WiFi or 3G/4G service to connect with zigbee communication gateways which, in turns, connect with each individual EV charging stations through zigbee communication protocol. The webserver and database server receive and send data through these hierarchical network connections. The mobile devices interact with the EV network through connection with 3G/4G or UCLA campus network.

The UCLA WINSmartEV™ smart charging infrastructure has five major components:

1) Smart charging stations,
2) Server-based control system,
3) EV User Mobile App,
4) Systematic safety integration,
5) Smart charging algorithms.

The following subsections describe the details of these components.

3.1. Smart Charging Stations

Current commercial EV charging stations provide basic stations without any network features or they use proprietary technologies to connect charging stations to networks. For instance, while Coulomb provides a ChargePoint application programming interface (API) and an Open Charge protocol for developers, the current application uses the company's own network to locate available charging stations for users. It is possible to build a smart charging system over a closed network with API and protocols; however, it is

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difficult to determine if such commercial implementations have an integrated safety design. We have implemented safety designs in basic, non-networked commercial charging stations, like those provided by Leviton and ClipperCreek. Nevertheless, these stations simply provide basic charging services without power information monitoring and network control features. In addition, the user must take extra steps in order to authorize charging sessions when using a closed system. Finally, commercial implementations like that of Coulomb may use smart charging algorithms in their charging stations, but these stations only have one or two outlets, which are not suitable for sharing electric current smart charging.

To achieve smart charging and collect data for this project, a single circuit connects the standard charging plugs in an electric vehicle supply equipment (EVSE) and provides four points for EV charging. We have deployed two types of EVSEs: level 1 chargers that connect to standard 120V household circuits, and one level 2 chargers that connect to 208V or 240V circuits for faster charging. We also have explored the design of controlling a level 3 charger in this project.

The following subsections describes the results obtained from this research and development of smart EV chargers.

3.1.1. Level 1 Charging Station

The Level 1 EVSE has 4 NEMA 5-15 outlets (EVSmartPlugs™) that allow multiplex charging up to four EVs at one time from a single conduit. All control happens by switching the outlets on and off, because the control system only regulates the 120V power to the smart plugs. Within this control scheme, authorized users start or stop EV charging sessions via a mobile device, while the centralized control server intelligently schedules charging. All communication spanning the charging box, EV owner, and control center occurs through wireless (3G, WiFi, ZigBee) or wireline (PLC, Ethernet) systems. We have successfully tested the level 1 EVSE on a Nissan Leaf, Chevy Volt, and Toyota Prius.

The level 1 EVSE comes in two versions: indoor and outdoor **(Figure 7** & **Figure 8**). Both chargers have passed the Los Angeles Department of Building and Safety (LADBS) Electric Testing Lab certification.



Figure 7. Indoor Level 1 EVSE

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Figure 8. Outdoor Level 1 EVSE

We developed the SMERC EVSEs to work in tandem with the WINSmartEV™ communication system. A control center monitors and controls a network of EVSEs, and it can independently manage the power usage of any charge point or groups of charge points on the network. The software based control system uses optimized algorithms for smart charging EVs. In addition, the end user can control charging sessions through a web app that enables remote scheduling and monitoring of charging status. The system can also produce reports and graphs that graphically display energy consumption for each charging station, and it includes support for conditional access systems, such as payments.

Since March 2013, we implemented significant upgrades to the outdoor device. We installed an outside switch for emergency power disconnect along with a circuit breaker and GFI inside the box (**Figure 9** & **Figure 10**).

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Figure 9. Emergency power disconnect

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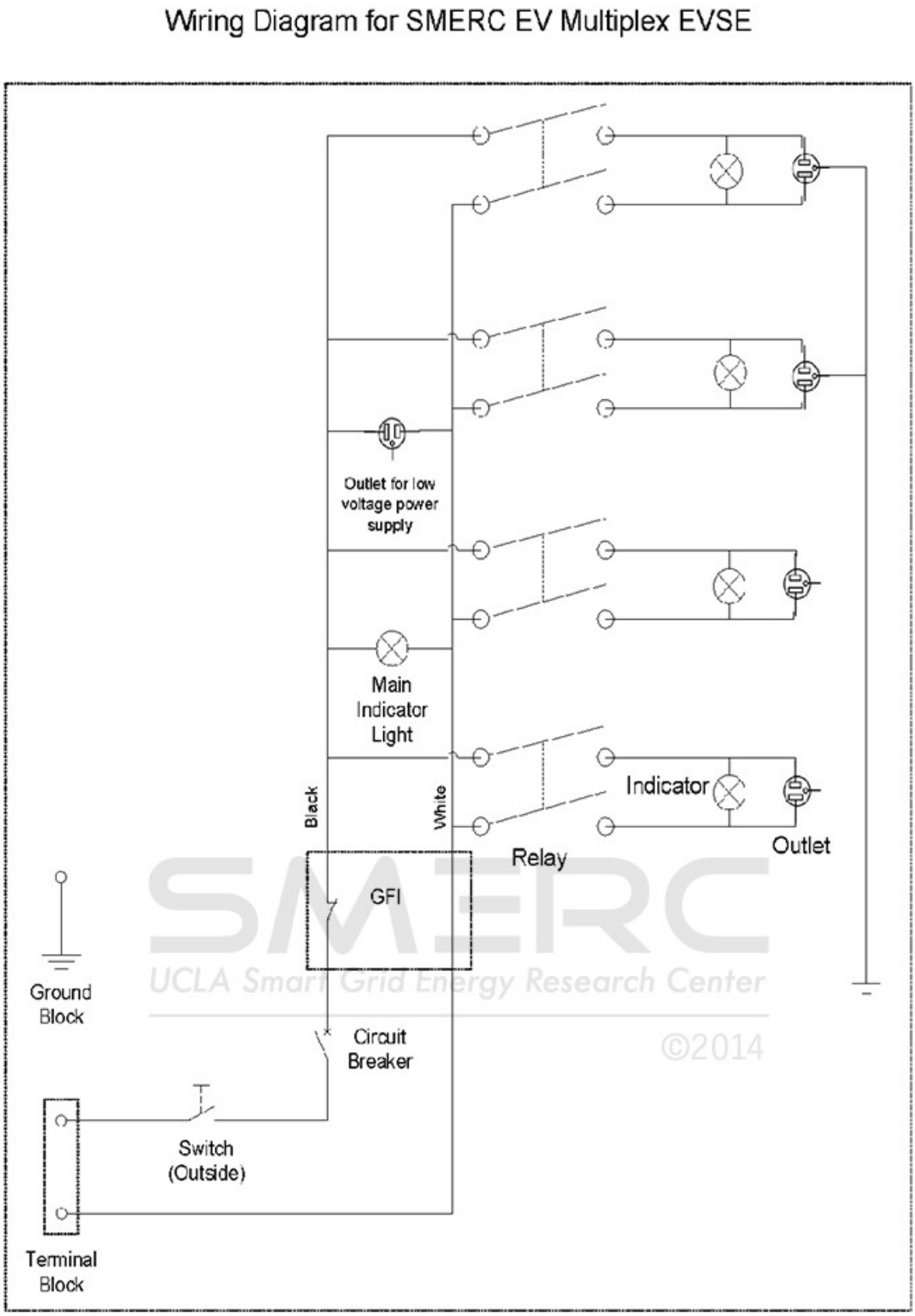


Figure 10. Wiring diagram for SMERC EV Multiplex EVSE

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We also redesigned the mounting process for the router and power supply in order to eliminate several holes in the EVSE's enclosure that could have resulted in a leaking problem.

The following are some specifications for the indoor/outdoor Level 1 EVSEs:

Physical

- 17.5" H x 13.4" W x 11.5" D
- Padlock Latch
- Submersible Fiberglass Enclosure (NEMA 6P/12)
- Wall or plate mountable

Electrical

- INPUT: AC 120V, 15A, 60Hz, Dedicated Circuits, Up to 4 dedicated circuits
- OUTPUT: AC 120V, 15A, 60Hz, Dedicated Circuit

Depending on total number of dedicated circuits wired into the level 1 EVSE, the control center can choose to multiplex the charging to connected vehicles alternatively or turn the charging (outlet) on all the time.

During summer 2013, we installed forty-two level 1 EVSEs in the Sunset Village parking structure (Figure **11**).

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Figure 11. Sunset Village installation

3.1.2. Level 2 Charging Station

The Level 2 EVSE has four J1772 connectors and cables with the capability of simultaneously charging four EVs. It uses the WINSmartEV™ communication network and integrates four channels of the pilot signal generator, real-time relay control, and plug-in detection circuits. All communication spanning the charging box, EV owner, and control center occurs through wireless (3G, WiFi, ZigBee) or wireline (PLC, Ethernet) systems. We have successfully tested the level 2 EVSE on the Nissan Leaf, Chevy Volt and 2012 Ford Transit Connect XL van. Figure 12 shows the details of the smart charger.

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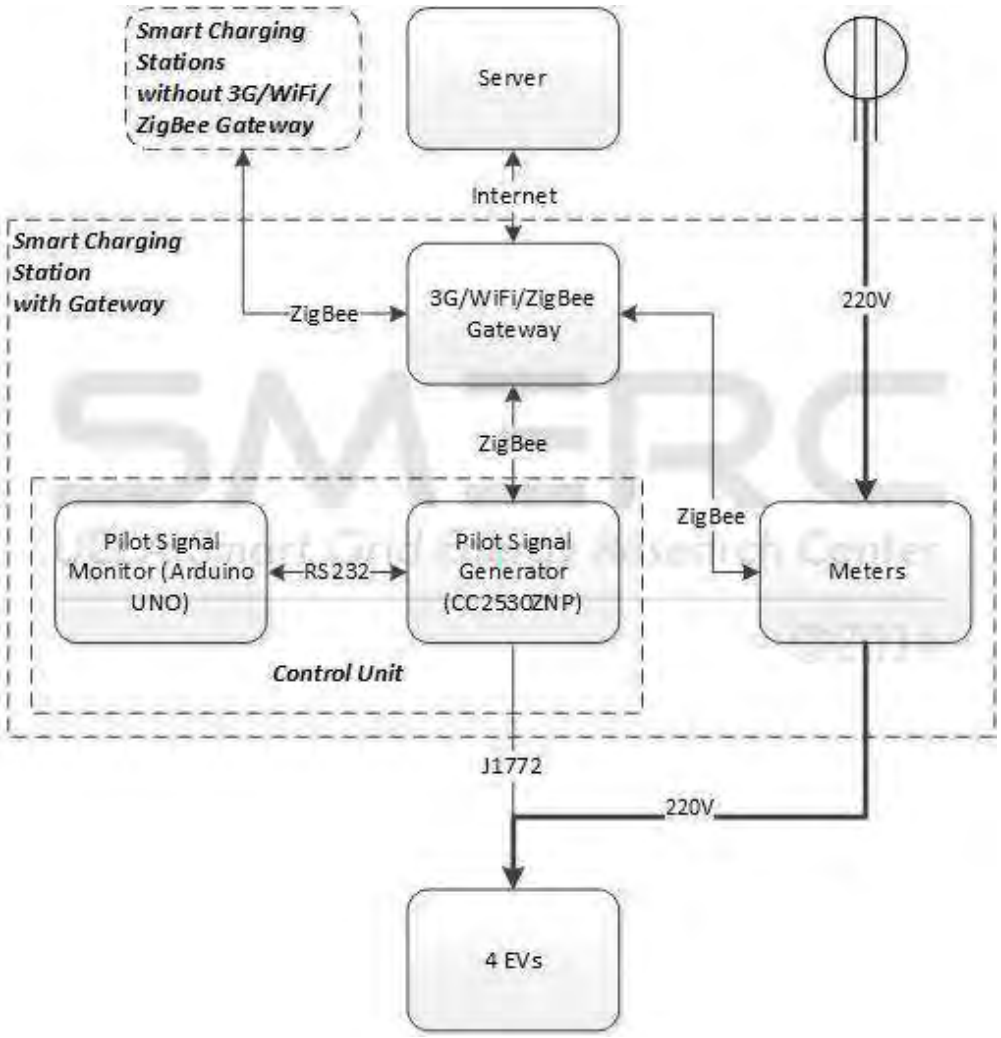


Figure 12. Details of the Level 2 EVSE

The Level2 charger consists of the metering system, communication modules, and the control unit. The meters return their power information to the gateway through a ZigBee connection upon receiving the command for retrieving power information. The ZigBee coordinator on the gateway manages the messages between the gateway and the end devices or routers including the meters, control units, and Vehicle Monitoring/Identification Modules (VMMs) [4] on the EVs. In order to dispatch the commands and parameters to the desired devices, the ZigBee coordinator needs to recognize and register the unique MAC addresses of the end devices or routers. One gateway per geographic location suffices, because a number of devices communicate using the ZigBee mesh network.

The control unit consists of a pilot signal generator and monitor. According to the J1772 standard [4], the pilot signal uses a Pulse Width Modulation (PWM) format with the power capacity information in its duty cycle. The EV adjusts its load to meet the power limitation of the charging station based on the duty cycle of the pilot signal from the charging station. A Schmitt trigger amplifies the PWM signal produced by the pilot signal generator from 3.3V/GND to ±12V, when fed to the EV. The pilot signal is de-amplified to within the A/D converter's range and fed through a low pass filter to produce a DC voltage for monitoring

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purposes. With this control scheme between the pilot signals and the EV, a current sharing algorithm on the level 2 smart EVSE becomes possible.

3.1.2.1. First and Second Design Iteration

We installed the first design iteration (prototype) in UCLA Parking Structure # 8. Based on tests on the first design iteration, we created a second design iteration. The second design iteration included the following changes:

1. DIN rail was installed inside the charger box to hold electrical parts.
2. Due to instability in the current GFCI system, a DIN rail mount GFCI breaker was installed in the charger to make it safe for immediate use.
3. Fuses were installed to separate the low amperage system from the high amperage one.
4. One wall wart was replaced with a hard wired power supply internal to the relay box, while the other wall wart was replaced with a DIN rail mounted power supply.
5. The indicator lights have been replaced by 240v lights, so as not to adversely affect the GFI breaker.
6. The long terminal block with daisy-chained wires has been replaced with a two legged terminal block and a distribution block.
7. All mounting holes in the box were removed for waterproofing.
8. In order to remove the mounting holes for the router and electronics boxes, a removable mounting plate was attached to the inside of the EVSE's enclosure.
9. A switch was placed on the outside for emergency cutoff.

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Figure 13. Level 2 EVSE with emergency cutoff switch on the right side

3.1.2.2. Third Design Iteration

We implemented the following changes into the third design, as shown:

1. Replaced the steel perforated sheet metal panel with a custom aluminum panel.
2. Removed all of the components from the lid, except for the indicator lights.

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3. Placed the electronic box #1, which houses the electronic components, on the aluminum panel with a cover held up by stands.
4. Installed a cover mounted on stands over the high voltage relays to protect personnel from unintentional contact while servicing. The cover is made from UL 94V0 rated U-channel.
5. Mounted the router to the high voltage relay cover.
6. Replaced the inline cap fuse holders with DIN rail mounted fuses.
7. Updated the low amperage distribution system for the current sensors with a distribution block that does not require daisy chains.
8. Replaced all zip ties with clamps and holders.

In addition, we changed the system so that all high voltage parts meet UL certified specifications. To achieve this goal, we replaced the relays that use 208V/240V coils with relays that use 12V coils. This update also required changing a number of systems, including the 12V power supply, which was upgraded from 1.67A to 5A.

3.1.2.3. Fourth Design Iteration - LAETL

In preparation for LAETL certification, the biggest change to the charger design came from implementing the donut sensor GFCI system. Through extensive troubleshooting, we determined that the 40A GFCI breaker system used up to this point caused the operational instability of the EVSEs. The GFCI breaker would trip under varying circumstances, causing the EVSE to go offline. Furthermore, the GFCI breaker caused failures during hipot testing. In order to solve these two problems, we replaced the GFCI breaker with a standard double pole breaker. To provide GFCI function, we designed a GFCI system that included CT sensors (donuts), connected to a GFCI sensing system and mounted into the electronics box #1, which would directly control the high voltage relays to shut off power in the case of a current differential. The GFCI system also included its own self-test system. This GFCI system solved the initial problems and increased the stability of the entire system whenever a fault occurs; the system reacts by halting current going into only one J1772 cable, instead of shutting down the entire EVSE. WE also made the following upgrades to accommodate the GFCI system within the existing architecture:

- Upgraded 40A Breaker
- Added current sensing donuts at the bottom of the plate
- Added self-test conductor loop
- Redesigned electronics box #1
- Added D25 connector and 8-wire bundle that connect the donuts to electronics box #1
- New Arduino shield integrated into the electronics box to control the GFCI test circuit

We also made improvements and changes to accommodate new relays in the high voltage circuit. The mechanical configuration of the available 12VDC coil, high voltage relays did not robustly hold all the required conductors, so we replaced the 12V coil relays with a 24VAC relay system; the relays also required a new 24V power supply. In addition, we replaced the old 12V power supply with a 12VDC unit, to support the new electronic requirements. To accommodate the larger size of the 24VAC power supply, we moved both the 12VDC power supply for the electronics and the 24VAC power supply to the backside of the plate. We also determined that the 24VAC power supply required a 400ma fusing system to protect

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and stabilize the entire low voltage system. We made the following changes to accommodate this upgrade:

- Updated the 12V relays
- Installed 24VAC transformer underneath the plate
- Installed the lower power 12 transformer underneath the plate
- Used the 24VAC signal to run updated indicator lights on the front of the enclosure

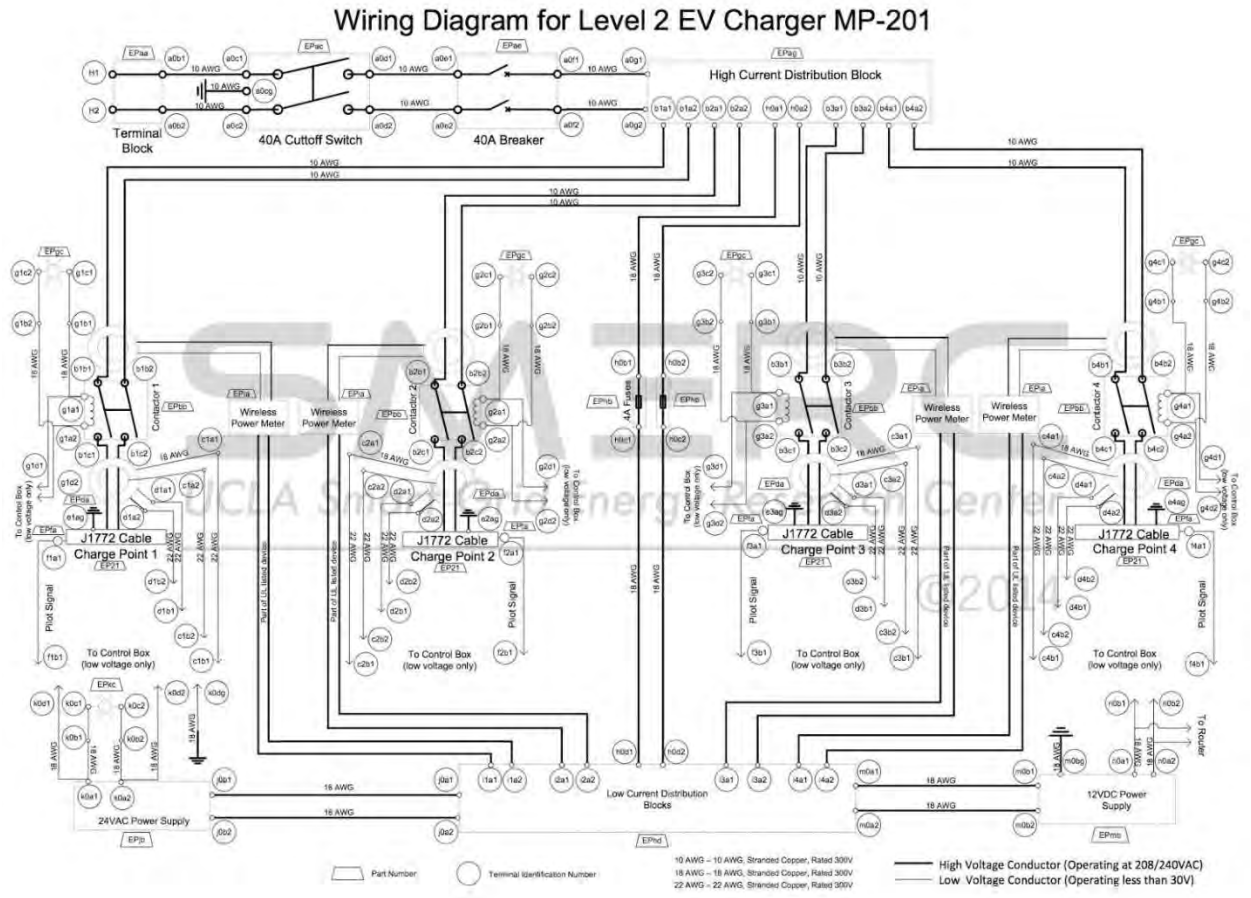


Figure 14. Diagram of low & high voltage circuits

Because of these changes, we had to reposition the components within the enclosure several times. For instance, it took three different iterations of the aluminum plate, on which we mounted the components, before we determined the final LAETL design. We also redesigned electronics box #1 to work with the new plate layout. We rearranged the components within the electronics box to allow for the addition of more connectors on the box. In addition, we cut ventilation holes into the top and bottom of the electronic box's lid in order to improve the airflow and prevent the relay module from overheating. We also covered the holes with aluminum mess to protect the electronics. We made the following electrical and mechanical changes to improve the assembly and operation of the charger:

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- Instead of using two single pole fuse holders, the box now uses a double pole fuse holder.
- Updated the pilot signal housing connectors
- Updated J1772 power cables to a newer version
    - Updated risers, that function as stands for cover of the high voltage relays, from 3” to 4” length
    - Added ¾” risers under the electronic box #1

In addition to the mechanical changes of the aluminum plate design, we redesigned the enclosure. We adjusted the position of the top power port to accommodate the new location of the terminal block and other changes to the aluminum plate. We tested various bonding agents to determine the best way to secure the aluminum standoffs that attach the aluminum plate to the enclosure. Furthermore, we mounted the 24V LED indicator lights on the lid of the enclosure with a lock nut and fastener system instead of silicone gel. This change better prevents the LEDs from falling out and improves the reliability of the design.

Moreover, we made several more changes to improve manufacturing, serviceability, and safety. We color-coded the wires throughout the entire system to make identification easier; each relay and indicator light has a unique pair of wire colors. We chose new wire paths to improve the separation of low and high voltage wires.

The following are the updated specifications:

Features

- 19.6” H x 17.6” W x 8.8” D
- Padlock Latch
- Submersible Fiberglass Enclosure (NEMA 6P/12)
- Wall or plate mountable
- All internal components mounted on aluminum plate

Electrical

- INPUT: AC 208V to 240V, 40A, 60Hz, single phase, 2 wire w/ground
- OUTPUT: AC 208V to 240V, 30A continuous load shared between four J1772 plugs
- Custom GFCI system
- Separated high and low voltage circuits

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Figure 15. Level 2 LAETL EVSE Cover

3.1.2.4. Documentation

We created extensive documentation to fulfill the LAETL certification requirements. We designed a new wiring schematic that uses a unique code to identify every single electrical component used in the charger and matches them to the bill of materials. We also labelled the important electrical components on the aluminum plate. Then, we created an assembly procedure manual that details the entire assembly and manufacturing process, including diagrams, photographs, and relevant wiring tables.

In addition, we developed an inventory management system to track the components used in the chargers. We created a numbering scheme for internal parts to identify all the components that went into the charger. The system includes the manufacturer's or vendor's number, the UL number, and SMERC's internal designation.

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Finally, we created an owner's manual that details how to install and use the EVSEs along with detailed specifications and product information. These manual will be included as part of the final report.

3.1.2.5. Fifth Design Iteration to meet requirements for UL certification

SMERC is currently prototyping the next generation of charger for UL certification. To improve upon the LAETL design, the lab is working towards advancing the functionality of the GFCI test and voltage detection circuit. To control the GFCI circuit, we add a second dedicated Arduino within electronics box #1; this additional Arduino requires reworking the positioning of the connectors on the box. The EVSE also has a secondary electronics box (electronics box #2) that acts as a voltage detection circuit for the relays.

Electronics box #2 primarily houses a voltage detector that tests the output of the relays to ensure proper functionality. This detection mechanism provides detailed feedback regarding the behavior and performance of the charging cycle. Before starting the charging process, the system needs to ensure that no power is at the outlet. When the GFCI event or user unplug event happens, the system can ensure that the power turns off properly before attempting the reconnection procedure. This feature must be added in order to pass the UL certification.

Due to spatial limitations on the back of the plate, the chosen electronics box has presented a series of ergonomic and manufacturing challenges. Electronics box number two must have high voltage entering it in order to measure that voltage. Because of this high voltage in the box, we determined that a UL certified box would be preferable. The only option that fits our constraints (Small & UL listed) is die-cast aluminum. We conducted a series of tests (drilling, punching, etc.) to determine the best way to manufacture this box. The proto type boxes have been preliminarily tested in the lab with EVSE testers.

As part of the development process, we had to redesign the aluminum plate again to make space for electronics box #2 on the back of the plate. The box will fit snuggly on the top back of the plate, along with the two distribution blocks, the 12V power supply, and the 24VAC transformer. We also routed the new wires in a safe manner to minimize the proximity of the high and low voltages.

The enclosure of the charger is also undergoing revisions. A tricolor indicator light replaces the single-color indicator lights on the lid of the enclosure. These new indicator lights are controlled by the electronics instead of the relay control signal or the relay output as in the current and previous versions. Using this design, users receive more information, such as ready to charge, charging, or error. This new indication system invalidates the fifth (main) indicator light and so, we remove it from the new design. These lights also require twelve conductors and connect to the electronics box with a DB-15 connector.

In summary, we make the following changes:

- Add second electronic box that will detect the voltage of the output of the high voltage relays and will send a status signal to electronics box #1
- Add 4 conductor cable to function as a communication pathway between electronics box #2 to electronics box #1
- Add a second Arduino into electronics box #2 to separate the GFCI safety system from the rest of the functionality

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- Replace single color indicator lights with tricolor indicator lights
- Add a DB-15 connector to the electronics box to connect the cable to the indicator lights
- Install additional control board to electronics box #1 to control the tri-color indicator lights

3.1.3. DC Fast Charger

3.1.3.1. Overview

The J1772 level 2 AC charging station developed in UCLA SMERC lab already has the ability to vary the charging current to the EV based on charging control commands that are sent from the control center. It also includes a multiplexing feature that can simultaneously charge four plugged-in EVs, either by evenly dividing the energy or providing each vehicle with different proportions. As battery capacities begin increasing with advancements in technology, the charging speed of the level 2 AC charging station will reach a point in the future where it will not satisfy the scheduling needs of customers, and DC fast charging will become more popular. Currently all the J1772 DC fast charging stations on the market can only charge one car at a time with a fixed current. In this project, we plan to develop a J1772 DC fast charging station with varying current and multiplexing features that leverages our experience gained from our work on the level 2 AC charging station. The DC fast charger along with its capability to support V2G operations makes it an excellent candidate for distributed energy resources (DER) and has great potential to play an important role in the future of V2G and frequency regulation market.

3.1.3.2. Approach

SAE J1772 specifies that the output current of the level 2 charging station is defined by the duty cycle of the Pulse Width Modulation (PWM) signal on the pilot control line. Most of the charging control signals between the EV and EVSE are exchanged via the pilot signal control line, but in the J1772 combo specification, the PWM signal on the pilot control line no longer plays such a role in the communication between the EV and EVSE. Instead, the EVSE and EV use a powerline-communication (PLC) system when performing DC fast charging. The PLC communication uses the pilot control line for message exchange, while the J1772 DC fast charging uses the XML language to transfer information. The schematics of the PLC communication system for charging control is shown in Figure 16.

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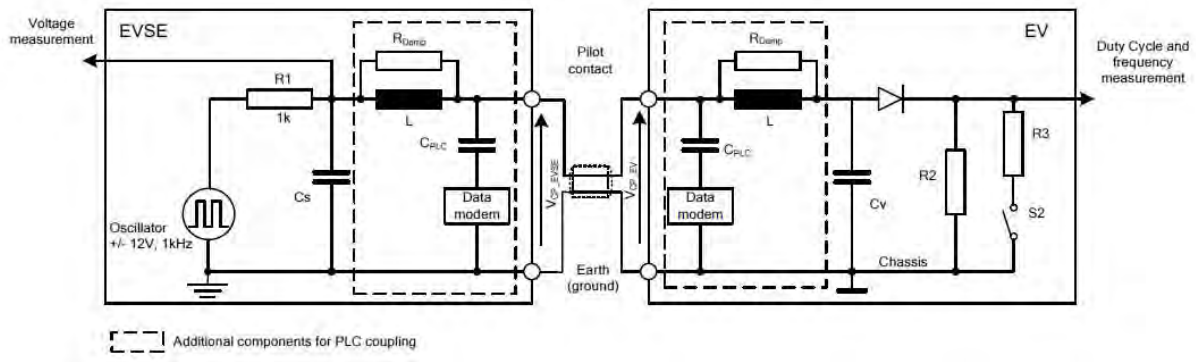


Figure 16. PLC between DC charging station and EV [5]

In a J1772 level 2 AC charging station, the duty cycle of the PWM signal on the pilot control line controls the output current. This relationship is shown in Figure 17.

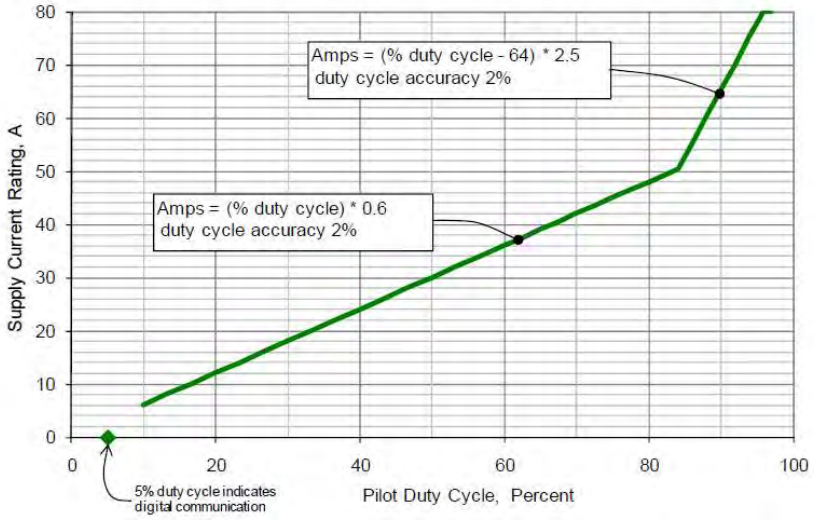


Figure 17. Supply current rating vs. pilot control duty cycle [6]

In a J1772 DC fast charging station, the duty cycle on the pilot control line is fixed at 5% during the charging process, which indicates digital communication, as shown in Figure 17. The digital communication occurs on the control pilot line by PLC using the HomePlug Green PHY 1.1 protocol.

Before DC fast charging station and EV begin the energy transfer, there is a handshake during the initialization process. This handshake process defines the charging voltage and current, and enables the EVSE and EV to exchange important charging parameters on the control pilot line, including the voltage and current limits that they can provide and accept. After the handshake, the contactor in the charging station will close and the energy transfer will begin. Figure 18 shows the charge current request signal and the charge current. The vehicle regulates the energy delivery by managing the Voltage Request and Current Request signals to the DC Supply with a cyclic message (7a). The DC supply reports its present

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output current and output voltage, its present current limit and voltage limit, and its present status back to the PEV in message (7b) [].

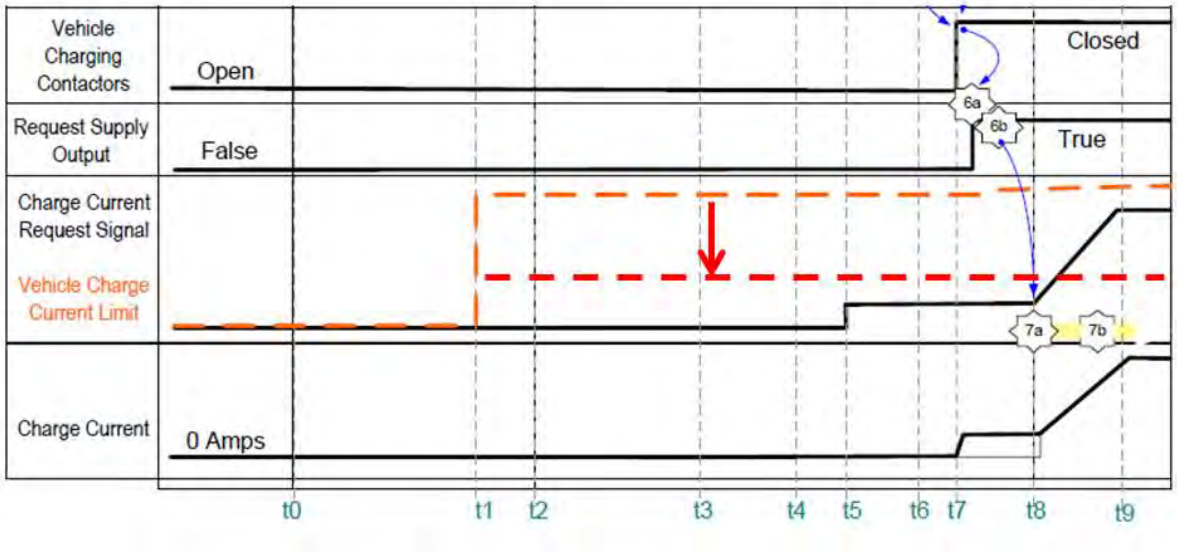


Figure 18. Charge current request signal and charge current [6]

The possibility of designing a J1772 DC combo charging station is based on the current request signal. In the case of the level 2 AC smart charging station, we can change the charging current by modifying the duty cycle of the PWM signal on the control pilot. In the case of the DC charging station, the EVSE and EV exchange information regarding the current and voltage request, and the limits of each device. On the EVSE side, we can design a feature in the hardware and firmware that can change the EVSE's output current limits as needed. If our smart charging algorithm requests a lower charging current, the firmware will tune down the output current limit value in the EVSE PLC message, as shown in Figure 18, then the EV will adjust its energy receiver to the lower current input. In this way, we can control the charging current in the DC fast charging process.



Figure 19. Multiplexing on DC fast charging station

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With the realization of variable current control, multiplexing current sharing in DC fast charging can be developed. As shown in Figure 19, the original output of one DC fast charging station can be multiplexed into several output channels, and feed multiple EVs simultaneously or one by one alternatively with the current limits signal correctly allocated to each plugged in EVs and controlling the total current within limit. Unlike level 2 charging station which can only charge 4 EVs one time at maximum, due to the fast charging feature of DC charging, one DC fast charging station may serve tens of EVs at the same time. This is because that it only needs 20 min to fully charge one EV and average parking time usually more than 4 hours in a work place parking.

3.1.3.3. Achievement and plan

As shown in Figure 20, a DC combo charging station (Bosch) was purchased for observation and to act as the test bed for smart DC charging station development.



Figure 20. DC combo charger purchased in the lab

In DC fast charging, EV and EVSE are communicating via control pilot line using HomePlug AV Green PHY 1.1 Powerline Communication (PLC) protocol as specified by SAE J1772 standard. In this project, a pair of PLC adapters are used to develop PLC communication features in the smart DC charging station. The PLC adapter pair is shown in Figure 21.

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Figure 21. PLC adapter pair for PLC communication design

According to J1772 Combo protocol, the DC charging station must be able to generate current limits message and send via PLC to the EV to control the charging current. The first step of establishing this communication is to acquire and analyze the PLC message exchanged between EVSE and EV. The approach used to acquire PLC charging control message is by connecting a computer with an EV emulator software installed on the EVSE control pilot line using a PLC adapter. The EVSE will consider the computer as a plugged-in EV and sending charging control message to the computer. The message will then be captured and stored by PLC utility software installed in the connected computer. The PLC utility software used here is Qualcomm Atheros Open Powerline Toolkit, which is used for controlling the Atheros PLC chip in the adapter to send, receive and listen to PLC messages.

In the UCLA SMERC level 2 charging control electronics design, the Arduino MEGA2560 was chosen as the main controller. Processing the voltage and PWM signal in the EV and EVSE communication needs a real time system to avoid possible delays which may result in safety issue and other errors. Arduino MEGA2560 has such a real time system feature. However, Arduino MEGA2560 is lack of ability to deal with high level communication such as PLC. So in the DC fast charging electronics design, Raspberry Pi is chosen to work as the main controller. Raspberry Pi is a micro-computer with a Linux kernel operation system. It can handle PLC communication. However, Linux cannot support real time feature in this case. To make the DC fast charging control electronics contain both PLC communication and real time feature, a master-slave controller configuration chosen to solve this problem. The Raspberry Pi will work as a master controller and connect with Arduino, the slave controller. Figure 22 shows the connected Raspberry Pi and Arduino current project development.

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Figure 22. Connection between Raspberry Pi and Arduino for capturing communication signals on DC fast charger

Raspberry Pi will handle most of the tasks while Arduino dealing with those tasks required real time feature. Raspberry Pi and Arduino must be able to communicate with each other. Figure 23 shows a flow chart of Arduino and python script written for Raspberry Pi to eatablish the communication.

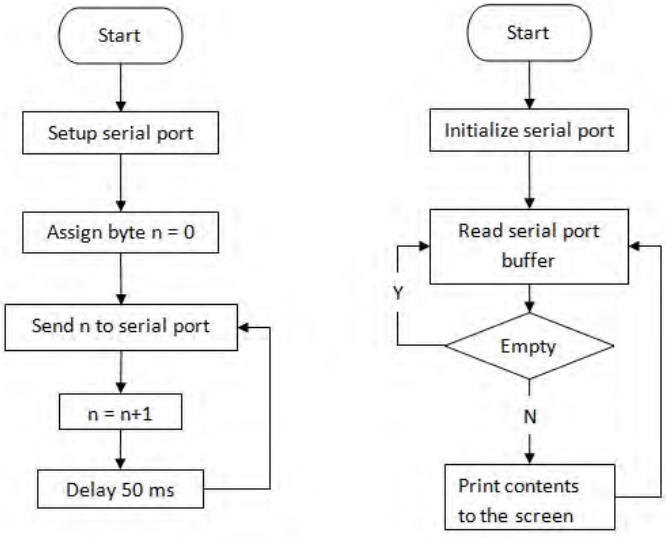


Figure 23. Flow chart of connection between Raspberry Pi and Arduino

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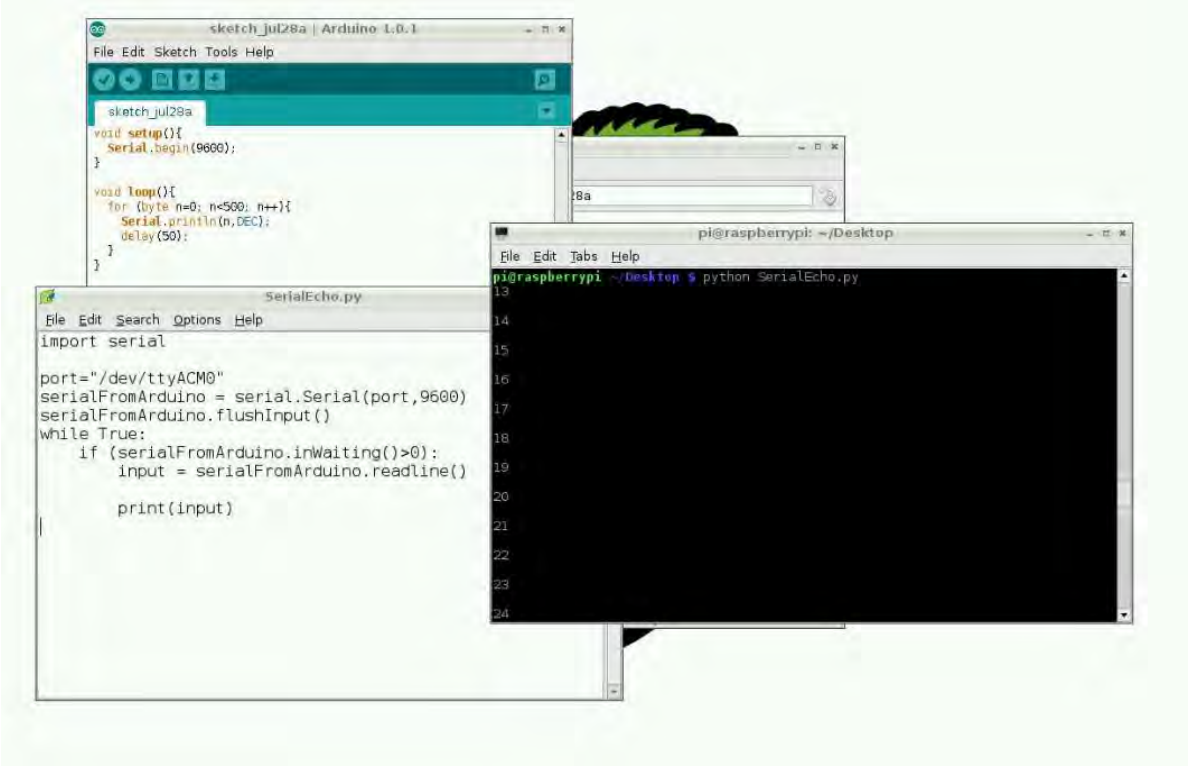


Figure 24. Arduino and Raspberry Pi communication on serial

In Figure 24, it shows that the program, which was uploaded into Arduino, sends continuous integers out to the serial port. The python script ran in Raspberry Pi kept reading its serial port which are connected to Arduino. In the terminal, the message from Arduino was captured and printed on the screen. The communication was established successfully.

The Raspberry Pi was then tested for its ability to capture and save PLC message. Once the communication is established, we can proceed to connect it to the EVSE to acquire charging control message.

Qualcomm Atheros Open Powerline Toolkit is an open-source utility made by Qualcomm Atheros to manage and control the PLC chip. Currently, we were able to use the Qualcomm Atheros Open Powerline Toolkit to execute commands on the PLC adapter such as monitoring the PLC network, transmission speed testing, etc. We can also use the port listening command to capture PLC command transferring between PLC adapter pair, as shown in Figure 25. The front terminal window shows the command transferred and the back terminal window shows captured PLC communication by the port listening program.

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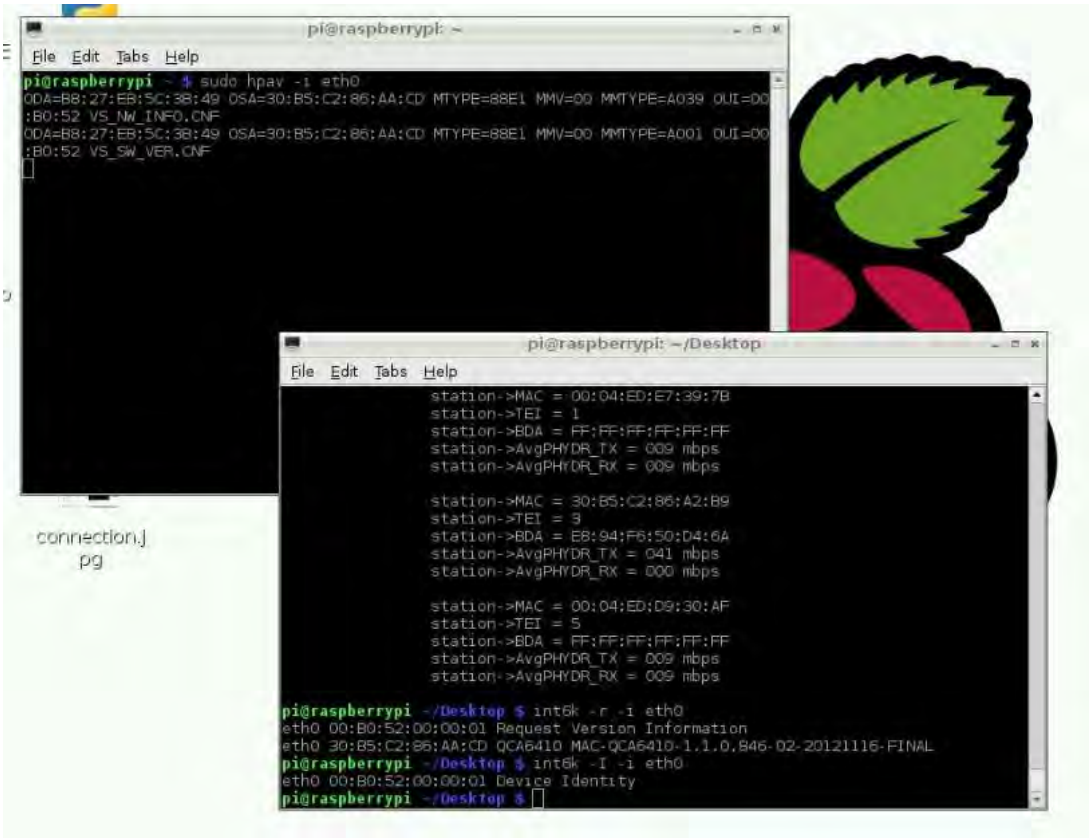


Figure 25. PLC connection test between two PLC adapters captured by Atheros Open Powerline Toolkit

It was found that the PLC devices use not only MAC address but also an identity number called Network Membership Key (NMK) to form PLC network and identify each other. All the PLC devices in one network may share the same NMK so they can talk in a private network. In the EV and EVSE communication, once the EV plugged in the EVSE, a temporally NMK should be generated to enable the connection. It is important that we can change NMK in the PLC device and form the network between devices from different manufacturers. By using the Atheros utility, we were succeed to change the NMK in the PLC adapters and form a network containing various PLC devices. Figure 26 shows the network formed with different brands.

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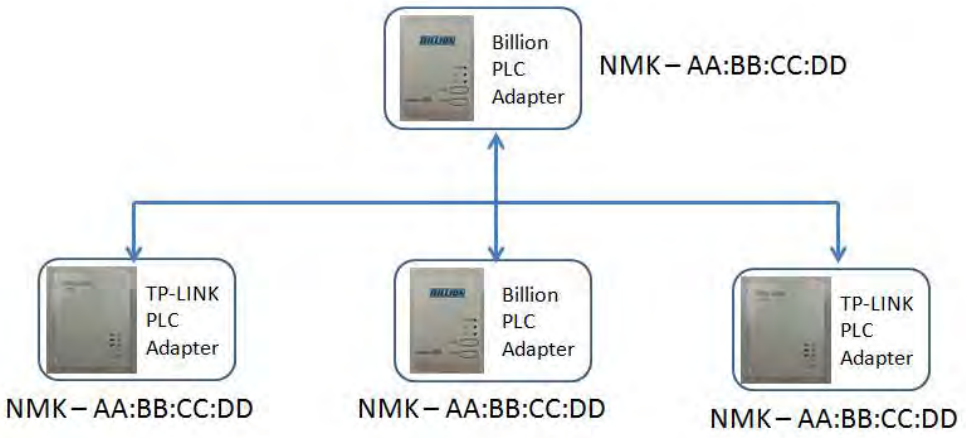


Figure 26. PLC network between adapters from different manufacturers

The network was formed by using the Atheros utility in Raspberry Pi, their NMK were all changed to 00:11:22:33:44:55:66:77:88:99:AA:BB:CC:DD:EE:FF, as shown in Figure 27.



Figure 27. NMK modification by Atheros Open-PLC utility

After the PLC devices from different companies shared the same NMK, they became immediately paired and worked together to form a network, without the need to push any pairing or synchronizing button. The capability of pairing PLC devices using NMK is very important when we connect our own control circuit to the EV and EVSE network.

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3.1.3.4. V2G and Frequency Regulation Design

DC fast charging can fully charge an EV such as Nissan Leaf battery from 0% state of charge to 100% in 20 minutes. The fast charging and discharging feature of DC fast charging make it a great source of distributed energy unit. With additional circuits integrated, when stay plugging in the DC charging station, EV can feed its power in the battery back to the grid when there is power shortage and fluctuation. When the grid is back to stable, the battery can resume its charging session. For frequency regulation, if there are enough plugging in EV serving as frequency regulation devices, the total regulation capacity can be beneficial to power grid. Bi-directional power flow design of DC fast charging station can make it possible for EV become distributed energy unit and hence source for frequency regulation.

The variable current and multiplexing charging features make the smart DC fast charging station a useful asset in reducing impacts to power grid. With multiplexing feature, one smart DC fast charging station can serve as an aggregator that feeds power from multiple plugged in EVs back to grid.

With proper algorithm designed for frequency regulation, the smart DC fast charging station can not only satisfy the user charging demand but also achieve maximum rewards from frequency regulation market. The algorithm is designed for providing control strategy of the charging station to decide charging/discharging rate and time. To this date, there has not been a commercial smart DC fast charger that uses J1772 Combo protocol to conduct bi-directional power flow for frequency regulation on the power grid.

The energy price and frequency regulation reward changes every hour in a day. Observing the energy price curve in seven consecutive days, it is determined that although there are some deviations between price curves throughout 7 days, the patterns of price variation are similar. The energy price and frequency regulation reward are plot in Figure 28.

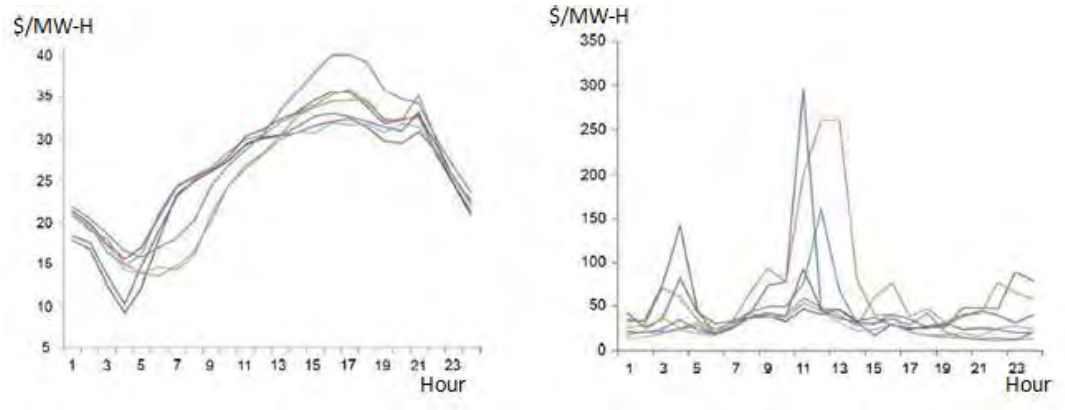


Figure 28. Seven days curves in one plot for energy price (left) and frequency regulation reward (right) [7]

From Figure 28, the energy price and frequency regulation reward can be modeled and the model can be used to predict the price in the next day or next hour. Assume the energy price can be modeled as $P_C(t)$,and the frequency regulation reward can be modeled as $P_R(t)$.

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We can set the total revenue from frequency regulation is R(T, r(t)), which has control variables of charging time and charging rate. An optimization can be perform to the frequency regulation revenue to maximize the value:

$$R(T, r(t)) \triangleq \int_{T-T_C} P_R(t)dt - M\int_{T_C} r(t)P_C(t)dt$$

$$\text{s. t.} \quad M\int_{T_C} r(t)dt = Q$$

The variables in the optimization are:

R	Revenue of frequency regulation
T	Plug in duration
T_C	Required time to reach target SOC
$P_R(t)$	Regulation rewards
$P_C(t)$	Charging energy price
M	Energy at maximum charging rate
r(t)	Charging rate, 0≤r(t) ≤1
Q	Required energy for target SOC

There are research works that focus on similar frequency regulation revenue optimization. However, all of these works are based on basic charging station which can only charge one vehicle at fixed charging rate as shown in Figure 29. When applied this optimization with the smart DC fast charging station, the charging rate variable can change between the range of (0, 1), and there are more than one EV providing frequency regulation service, hence a more flexible and better optimization result can be obtained. Further, when this optimal control strategy is designed and integrated into the smart charging algorithm in UCLA SMERC's smart charging control center, the frequency regulation capability of our smart charging infrastructure can be more beneficial to power grid.

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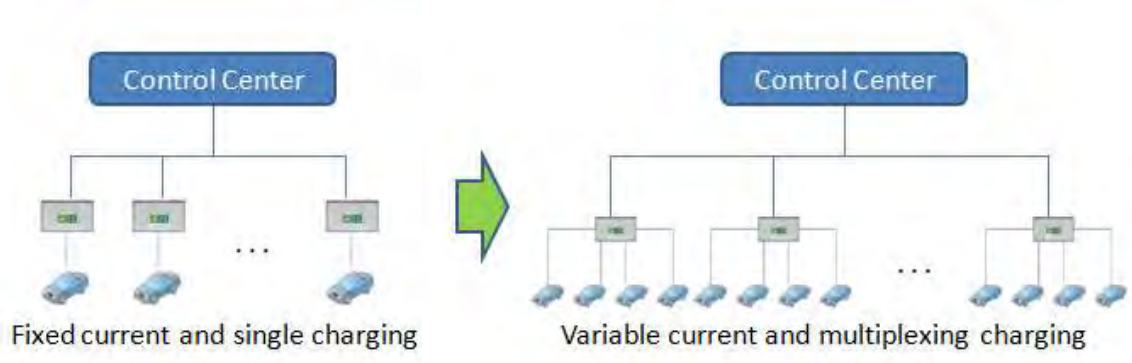


Figure 29. Comparison between smart charging station and basic charging station in frequency regulation

3.2.Server-based control system

A server-based control system regulates all charging stations through gateways that support 3G communication, which allows network communication as long as a cellular signal exists, because in some places wired or WiFi communication is unavailable. The system comprises the following software components: API 2.0, Station Controller and Data Collector built on top of API 2.0, System Monitor and Control Center, Database, and Mobile User App.

3.2.1. API

For monitoring and controlling our charging stations, we have integrated the aforementioned API into the control system, which defines the patterns of communication and transmission of control signals to EV charging stations. Our design of API stems from the concept of OOP (Object Oriented Programming). We model the complex communications and control behaviors of charging stations as logically distinct classes; for instance, the EVSE class comprises the EVSEs and charging plugs of different levels, Charging utility class provides functionality for web services and web-based applications, and the Charging Algorithm class regulates the charging behaviors within control loops. We developed the API on the .NET framework and compiled it into dynamic-link libraries (DDL), which we can also implement in other languages, such as C++ and Visual Basic. This format provides a convenient scheme for developers to derive more EVSE and charging algorithm classes with different properties and methods. This format will also save time and energy for system administrators to maintain the EV charging system. In addition, we have also implemented other modules for use in charging utility, such as a security module that ensures incoming function calls meet the system's security requirements.

3.2.1.1. EVSE Class (charging box and charging station)

The logical base class SMERCChargingBox models an EVSE with basic properties and methods that transfer to inherited instances. The class specifies common attributes of EVSEs (e.g. gateway ID, gateway IP address, and parking lot ID) and control parameters for charging algorithms (e.g. power source properties, charging algorithm ID, and control loop interval). In addition, we included a child-level class SMERCChargingBoxG1, inherited from the base class, to add several new EVSE-level functions, including enabling the local algorithm and retrieving the EVSE's power information via the JSON format. We can also distinguish Level I and II EVSEs, by specifying power source parameters of higher values and the charging algorithm's ID when creating instances of the EVSE classes.

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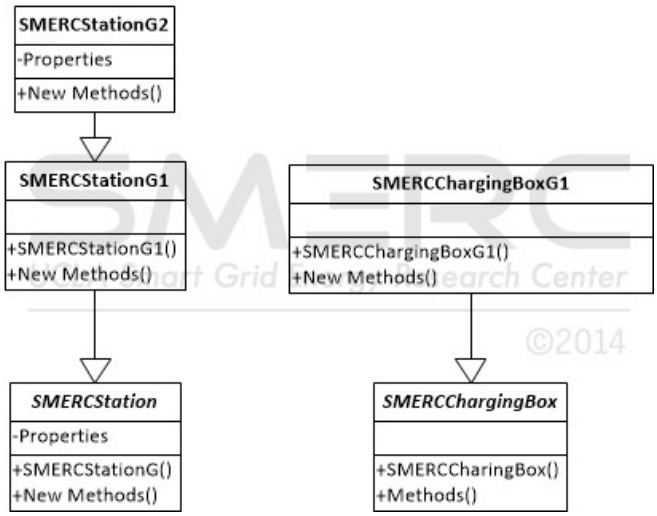


Figure 30. EVSE classes

The base class SMERCStation defines common properties and methods for all charging plugs in our system. The class includes general attributes that define a specific charging station (e.g. station ID, gateway ID, and power course ID) and attributes for charging algorithms (e.g. controllable status, base main energy value, and start main energy value). As inheritors of the station base class, we also define SMERCStationG1 for a level 1 station and SMERCStationG2 for the level 2 station.

3.2.1.2. Charging Algorithm Design

A charging algorithm performs a sequence of control commands at a specific charging station to regulate charging behaviors. These charging behaviors include starting and stopping charging sessions, retrieving power information and meter status, and adjusting charging power for an existing charging session to satisfy time-varying constraints, such as real-time electricity prices, availability of power supply, and the dynamic properties of EV drivers' traveling patterns. To accommodate such varying constraints requires implementing a flexible design for charging algorithms. Our implemented charging algorithms fall under two categories: the base class and current charging class. The base class contains the methods for an algorithm to interact with the database, communicate with charging hardware based on the HTTP protocol, compute schedules based on constraints, and provide other business functions. Therefore, we can use the base class template to create algorithms with varied purposes, each with its own distinct rules and logic. The current charging class provides the methods for performing different charging functions as listed below:

- SMERCBaseChargingAlgorithm
- SMERCChargingBoxG1Level1RealTimeOdometerAlgorithm
- SMERCChargingBoxG1Level1RoundRobinMultiPowerSourceAlgorithm
- SMERCChargingBoxG1Level2EqualChargingAlgorithm
- SMERCChargingBoxG1Level1PriceBidAlgorithm

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- SMERCChargingBoxG1Level2PriceBidChargingAlgorithm

3.2.1.3. Scheduling Service Design

According to experiment and data collected from our prototypical system, the implementation of a smart charging algorithm should meet four requirements. First, the design must switch between different charging algorithms. Second, it must dynamically update parameters of the charging infrastructure. Third, it must interact with the database, which contains real-time information for the constraints. Fourth, the design must allow for convenient updates and maintenance. A good solution meets these requirements using a Windows Service that ensures compatibility with the existing development environment. Figure 31 shows the design flow of a charging algorithm.

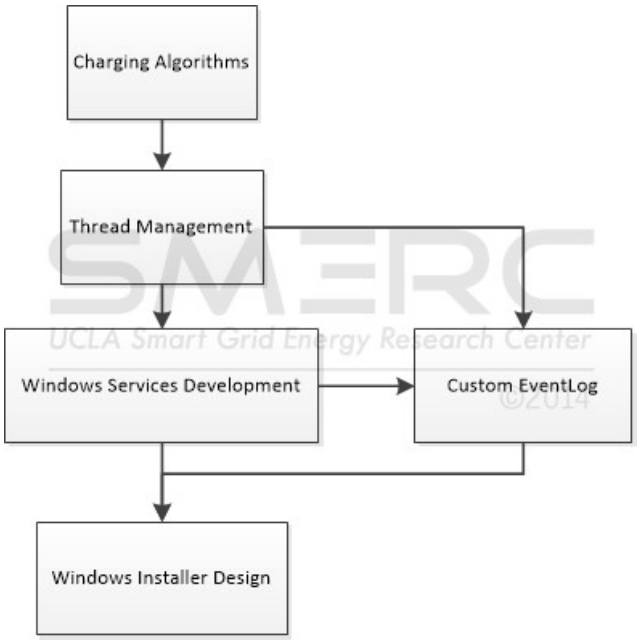


Figure 31. Design flow of charging algorithm

As shown in Figure 31, upon starting the service to manage EV charging sessions, each EVSE assumes a unique system thread, which prevents interference between each EVSE. In other words, the thread to manage each charging box works independently and any exception in one particular charging box will not cause the whole system to crash, which improves the system's reliability. To monitor and keep track of any exceptions for the program, each thread has a function to send program exceptions to the system event log. This method allows the system administrator to monitor and verify the status of the charging service program. A separate installer project, designed for .NET compatibility, deploys the service as an installer package.

3.2.1.4. Demand Response Service

For DR operation support, the interfaces for both open source demand response server provided by Electric Power Research Institute (EPRI) and third-party DR publisher, such as Super Control Center that is developed by SMERC to manage numerous loads and resources within UCLA micro-grid, have been developed, as shown in the Figure 27. OpenADR events standardized communications between virtual

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top node(VTN) and virtual end node (VEN) are supported. In addition, proprietary protocol defined non-public organizations are also work with our DR interfaces. The DR events specifying starting time, duration and the intensity (curtailment or throttling) are encoded in the event message and will be stored into the database system, associated with specific EVSE. Thus, the charging algorithms managed by scheduling services on server are capable of integrating the real-time demand response signals from database and regulate the charging sessions accordingly. DR services enable different types of organizations operate charging sessions using different preset modes and the real-time monitoring data based on this algorithm will also be kept in storage for other advanced algorithms.

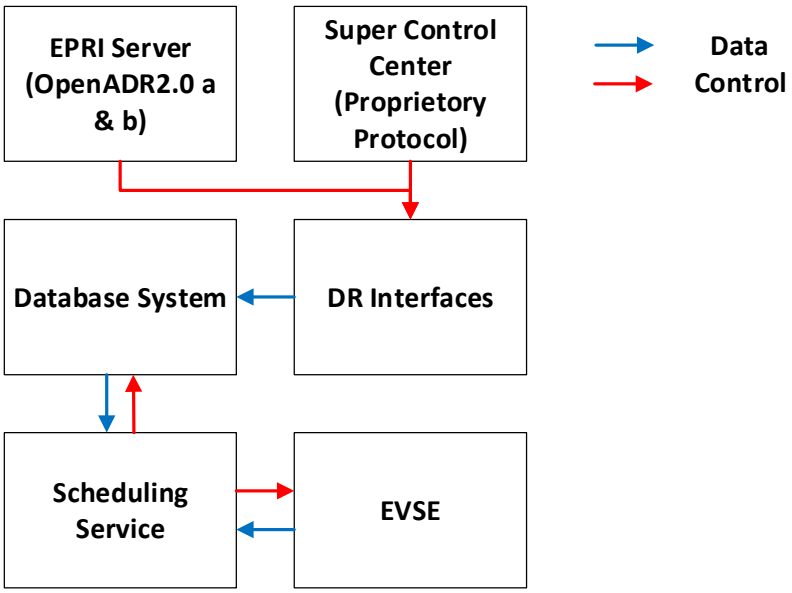


Figure 32 Overview of Demand Response

3.2.1.5. Security Concerns

We added several security modules inside API 2.0 as filters to improve system security level. We implemented these modules as a deliverable dynamic-lite library with connection capabilities to the database and charging infrastructure.

- Gateway Access Authentication

Each gateway mounted in the EVSE has an integrated feature for user access control, which requires a username and password to access and manage the gateway. We integrate this gateway feature into the data-model of our database design, and store the corresponding usernames and passwords as attributes of each EVSE, which are invisible to external parties after API compilation. Therefore, any action performed on the gateway requires the EVSE's username and password. This design effectively prohibits other parties from accessing our gateways in the parking structures.

- Gateway Access IP Range Constraints

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As a secondary security measure, we limited access to a range of IP addresses. IP addresses that fall outside the confined range cannot initiate communication with our charging infrastructure.

- Email Credential

Certain functions within API 2.0 require the system to notify EV users of their energy consumption and charging costs, which presents a user privacy issue. We utilize the cryptographic service from the .NET framework to perform authentication and authorization functions using secret and shared keys. Any attempt by an API function to send an email to an EV user requires the secret key to pass the security verification.

3.2.2. Station Controller and Data Collector Communication Protocol

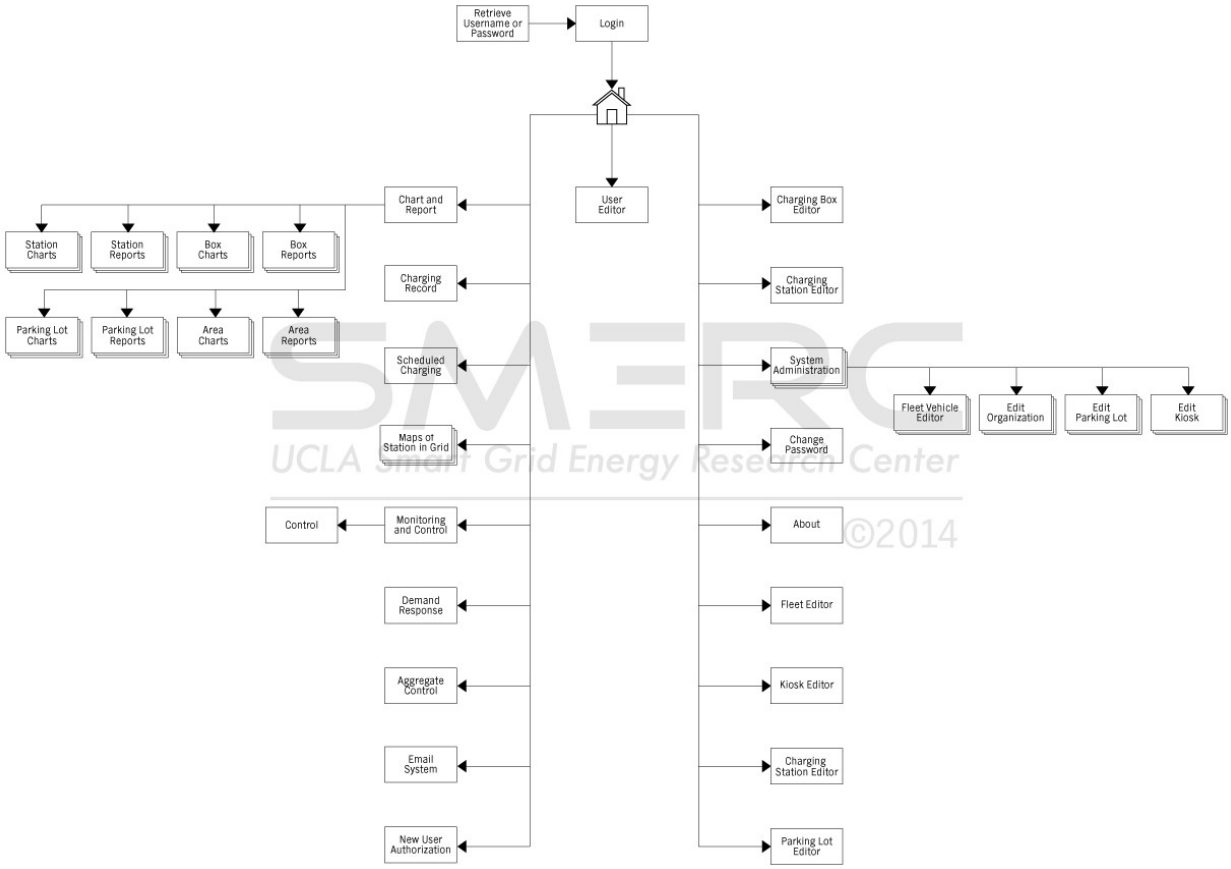
The Station Controller automatically controls the charging stations based on the selected charging algorithms, while the Data Collector collects the power information from the charging stations. We designed the API function RetrieveBoxAllStationsPowerInfoAndStatus into the charging algorithm template to retrieve power and station status information for each charging station, associated with a gateway. Once the retrieval completes, the function SaveAllStationsPowerInfo automatically saves all power information (e.g. station voltage, current, and active power) into the database's [station Record] key and labels each record with a timestamp value.

In addition, we added another function in JSON format to retrieve power information using the updated gateway's firmware. We can retrieve power information and meter status for all charging stations associate with a gateway using only one command. The gateway then returns nested data that the function parses in JSON format. We are still testing this function for reliability and system compatibility issues.

3.2.3. SMERC Monitoring and Control Center

The SMERC Monitoring and Control Center is a high performance server that allows administrators/operators to monitor and control all EV charging stations, registered to the network. The system defines control algorithms, provides real time and historical data for analysis, and allows the editing of information pertaining to charging boxes and EVs. The sitemap in Figure 33 shows the current features that are accessible after logging in.

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Figure 33. Monitoring and Control Center site map

Currently, the Control Center server platform is hosted on a high performance server and the system has been updated to API 2.0 mentioned in this report.

3.2.3.1. Station Map API

As shown in Figure 34, we have designed the control center's Station Map function based the desktop edition of Google map. It works fine in a desktop environment, but it is not suitable for two-finger zoom-in nor does it support gestures very well on the iPad due to its limitation of screen size and lack of pointing device such computer mouse.

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Figure 34. Current implementation of Web-based Station Map on a Laptop based Control Center

3.2.3.2. ZigBee API Configuration

The project aims at integrating a ZigBee meter with the existing SMERC Monitoring and Control Center web application in order for data, such as the mac number, model, voltage, current, and power details, to be updated automatically on the customer cloud server. The data is received from the ZigBee meter in JSON format, which is translated into the data format that can be stored on the server for further use. This will reduce the computational and communicational burden of Control Center.

3.2.3.2.1. ZigBee Meter and Gateway

The ZigBee meter allows monitoring and automation of energy usage by giving consumers the information needed to track consumption. The meter data is received by the Billion router device which provides an API to store the data on the server. The API also contains a feature, which sets the post interval that regulates when the ZigBee gateway sends the data to the customer server.

3.2.3.2.2. Data Reception

The algorithm template for the Level 2 charging box has problems when it controls charging. In particular, the data collector retrieves incorrect data. As part of our solution, we are trying to update the polymorphic methods.

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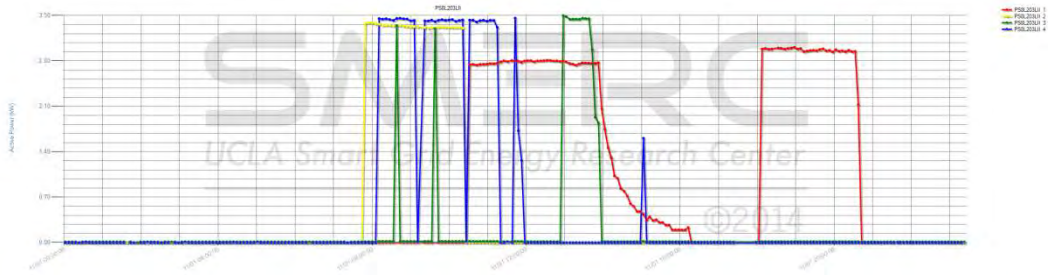


Figure 35. Incorrect data retrieval for Level 2 EVSE

The following are general ways used to check if data are correct or not. But there could still be error even though the overall error rate is reduced. We assume that electric current data are always correct and use it to double check if other points are valid. With such an assumption, there should be some relationship between other statistics and the current. If any data for a station is not correct at a certain time, all data at that time are regarded as invalid for the given station. For example, we assume that:

$$Voltage \times Current \times (1-\xi) \leq ActivePowe\ r \leq Voltage \times Current \times (1-\xi)$$

where threshold ξ is the allowed error (ξ is set to 5% in the program). This approach detects many invalid points of data. The difference in the production of voltage, current, and the active power can exceed 60%.

Another problem is that different stations are reporting statistics using one station identifier. As shown in Figure 36. Incorrect data for energy consumption, the energy consumption is constantly switching between 0 and 300+, which is impossible. To solve this problem, the latest main energy is checked. If the previous energy reading is larger than the latest one, that point is marked as incorrect. However, this approach does not work all the time, because when two stations are reporting their data with the same ID, the main energy of the station identified by the ID is constantly switching between two values. If both values are less than the latest main energy reading of that station, the system will still not determine which value is correct.

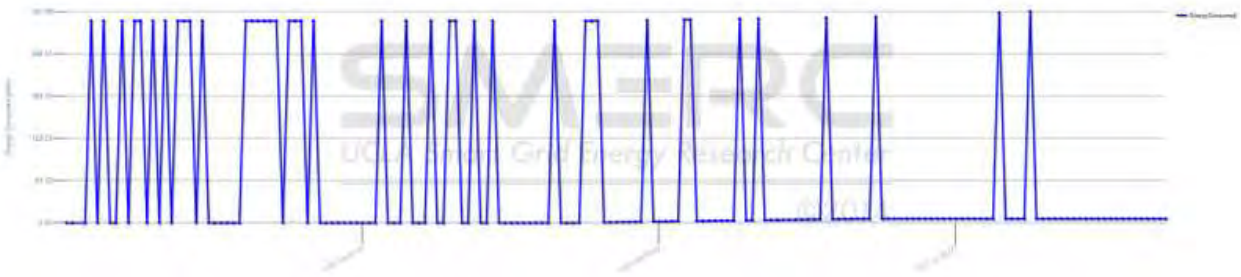


Figure 36. Incorrect data for energy consumption

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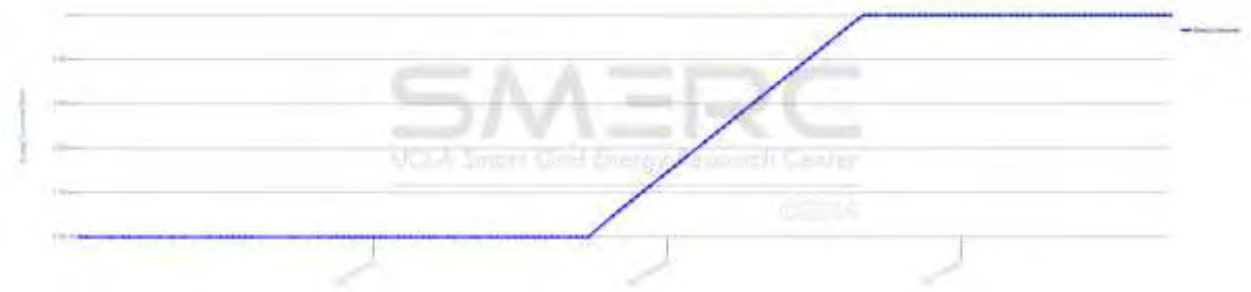


Figure 37. Filtered data for energy consumption

The main energy should always be increasing with the latter data being larger than or equal to previous data. The verification process makes sure of this and helps to smooth out the lines. Without verification, there will be some data points that are much larger than others or much smaller than others.



Figure 38. Chart displaying unfiltered data for energy consumption

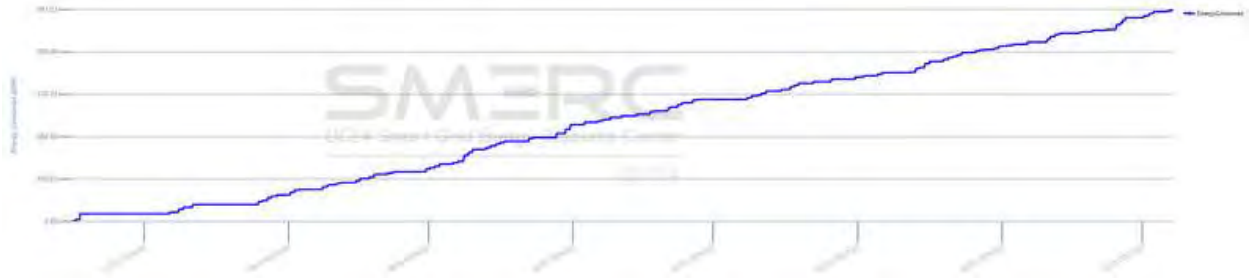


Figure 39. Chart displaying filtered data for energy consumption

Aside from the verification of station statistics, the charging records also need to be verified. In some cases, the final energy consumption is smaller than the initial energy consumption. In this case, the system will try to retrieve the station record, whose time is just before that of the wrong charging record and read the main energy in that record. The main energy will be regarded as the final energy reading for that charging record.

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3.3.EVUser Mobile App

3.3.1. Web-based EVUser Mobile App

EV owners can control the charging sessions of their vehicles through a mobile app or any other device with internet capability. The following are the basic features available in the current mobile app:

1. Check charging station Availability
2. View a map of stations
3. Start and stop charging sessions
4. Check charging status and records
5. Schedule a charging session
6. Check or cancel a scheduled charge
7. Change password or settings under setup

We integrated the updated API 2.0 into the web-based App and we are currently working on integrating the 3rd generation GUI into the EVUser Mobile app. We have also modified the interface to support the new algorithms in development. Figure 40 shows the new features available through the web-based app:

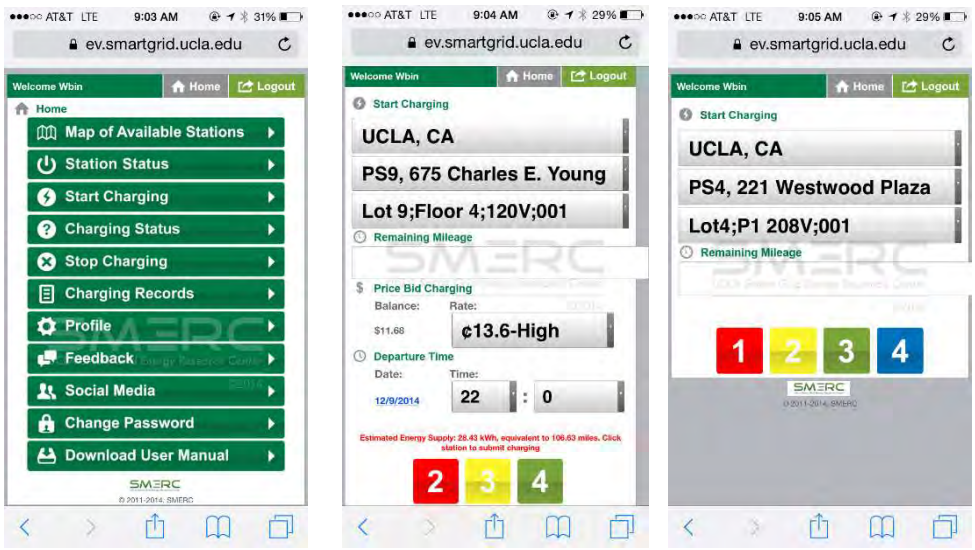


Figure 40. EV User Mobile App

- Input User Charging Preference

We added web controls in the Start Charging page to support price-based charging algorithms. The charging profile consists of two main components: 1) price preference, i.e. maximum accepted electricity price, and 2) estimated departure time. The system remembers the input from the previous charging session and selects it as a default profile, which saves time for the user. Once the user completes the profile, a prediction algorithm on the control center will automatically compute the predicted energy consumption and equivalent miles according to the user's profile. The user can start the charging session based on the predicted schedule by clicking a charging station icon.

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- Input Remaining Mileage:

Our mandatory user agreement requires that users input their remaining miles in the Start Charging page in order for system to record the remaining states of charge in the EV batteries and their energy consumption. Validation code in the web app will return an error message, if the input does not fall within a reasonable range.

3.3.2. iOS and Android EVUser Mobile App

Other than the web-based mobile App for users to manage their charging sessions, we are also developing an iOS version, which is supposed to offer a better user experience, including responsive touch controls and more interactive actions. Based on the library of Swift languages provided by Apple, more functions, such as Navigation to charging stations, will be designed to provide more convenience for EV users. Similar to the web-based App, the control and display logic will guide the users to input their charging preferences step by step. After a user logs on through the App, the modified home view is presented in Figure 41. Navigation is a very significant function we have developed in the latest version, which will automatically provide links for each parking lot at UCLA with SMERC charging EVSEs and build connections with the Apple map navigation system. Thus, users are able to follow the highlighted routes on the map to initiate their charging sessions. Other functions remain similar to the web-based app, as shown in the figure.



Figure 41. iOS EVUser Interface

The iOS mobile App can be downloaded from this URL: https://itunes.apple.com/us/app/smerc-ev-charging-user/id1033054597?ls=1&mt=8

A similar mobile App has also been created on Android platform. It contains same sets of functions and user interface design for consistency.

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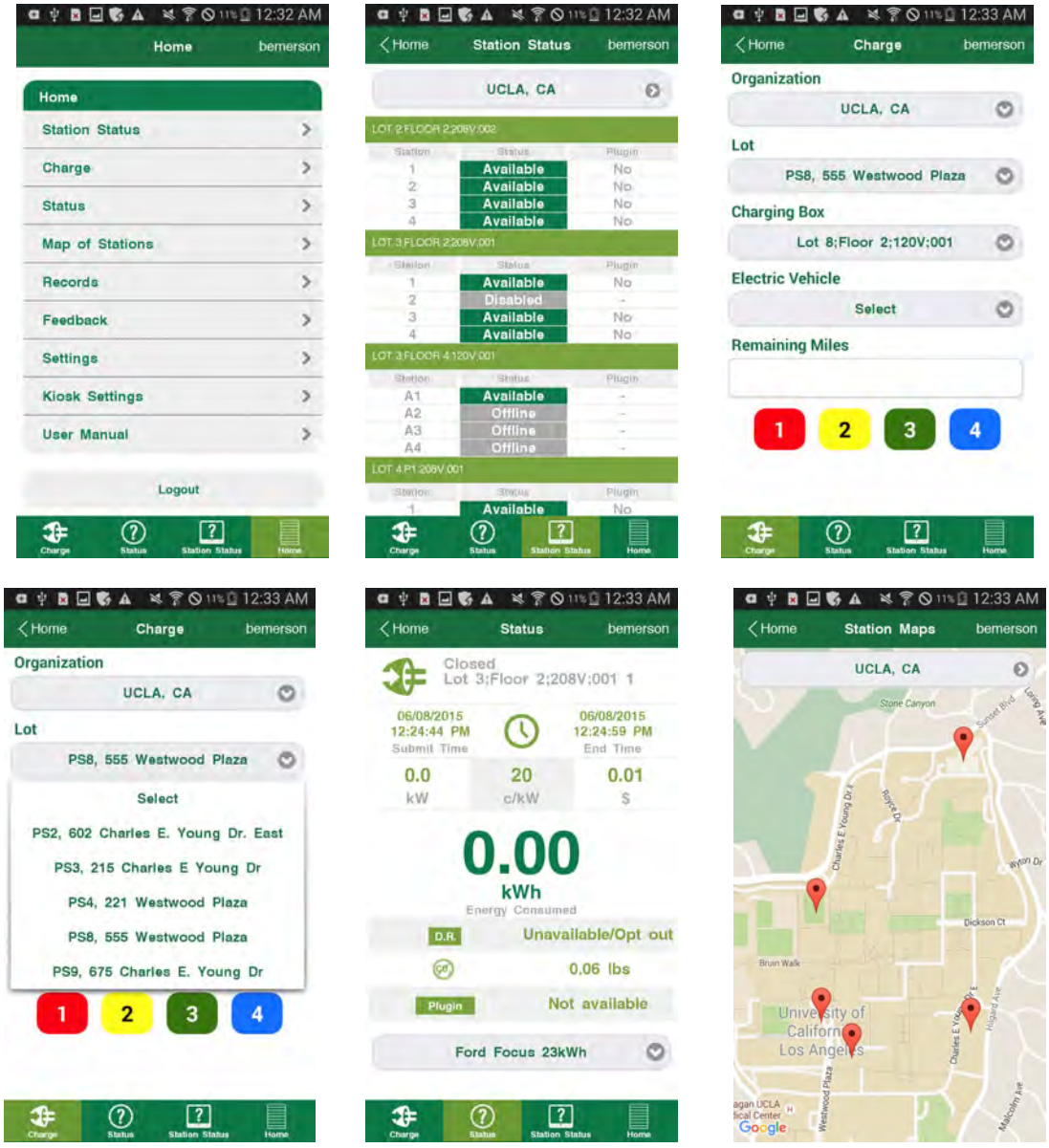


Figure 42. Screen Shots from Android mobile app.

3.4. Systematic Safety Integration

To provide a safe smart technology for charging EVs, a safety system has been designed for all levels of control. The administrator can turn the relays of the charging stations on or off and check their status by transmitting commands. The charging stations can be reset manually or automatically on schedule as long as the connection between the server and the charging stations exists. Any emergency action taken at the top level will have a delay time that depends on the condition of the wireless communication including 3G, WiFi, ZigBee, and Cloud. Thus, a fast acting local unit is implemented to stop charging in case of an emergency.

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In order to prevent electrical hazards, there should be no voltage on the handle of the charging cable until it is plugged into an EV. The detection of the EV plug-in status is implemented in the state machine of the firmware of the control unit based on the J1772 standard. The voltage of the pilot signal [6] pin on the handle should be +12V when there is no EV connected to the charging station. After plugging in the EV, the voltage will be +9V or +6V depending on whether or not the EV is ready to accept energy. The EV plug-in status detection is implemented in the state machine in the firmware of the control unit. Furthermore, the charging station is required to shut off the power immediately to prevent the hazard of electric shock when there is an abnormal diversion of current from one of the hot wires. The Ground Fault Circuit Interrupter (GFCI) detects the difference of current between two hot wires and shuts off the safety relay when the difference has crossed the threshold amperage. Unlike a traditional GFCI which requires manually pressing the reset button, a pure hardware GFCI with a remote reset function is used to in recover the charging session in case of a ground fault. The power to the EV can be controlled by the server, the control unit of the charging station, and the GFCI circuit as seen in the schematic in Figure 43.

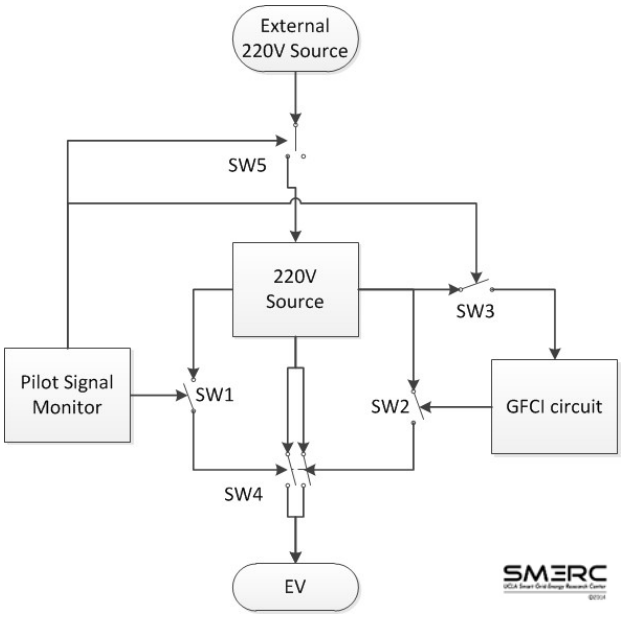


Figure 43. Schematic of safety control for the relay

One leg of the safety relay's (SW4) coil is controlled by the pilot signal monitor, while the other leg is controlled by the GFCI. The pilot signal monitor can reset the GFCI and the system by SW3 and SW5 when receiving the command from the server, which fulfills systematic safety integration.

3.4.1. Safety Design for Smart Electric Vehicle Charging with Current and Multiplexing Control

The following sections describe the experiments we performed to verify the detection of EV plug-in status and GFCI.

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3.4.1.1. EV plug-in status detection

In this experiment, the A/D values at the pilot signal monitor are measured with different duty cycles under two cases: “EV charging” and “EV disconnected”. The test-bed is a Nissan Leaf with 110V charging cable. Figure 44 shows the setup of the experiment and Figure 45 shows the results of the experiment.



Figure 44. Experimental setup for changing current by duty cycle

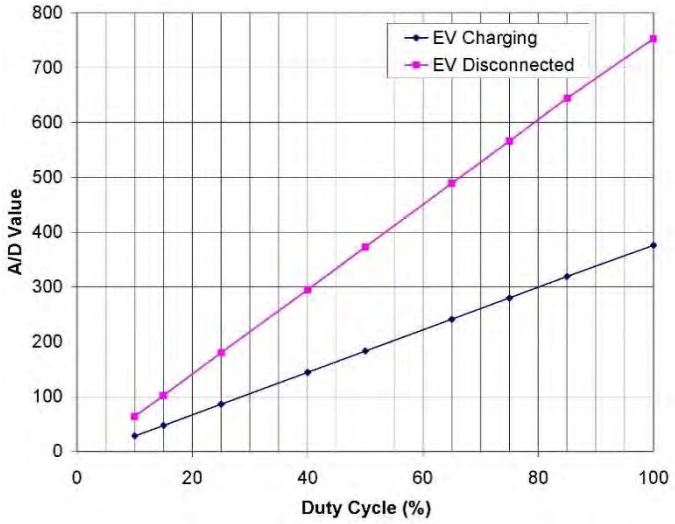


Figure 45. A/D Value v.s. Duty Cycle of Pilot Signal

The results show that the A/D values of these two cases are clearly distinguishable and have good linearity. Even when the duty cycle is around 10%, which is 6A, (the minimum charging current of the J1772 specification), the pilot signal monitor’s resolution is still more than sufficient to detect the EV’s plug-in status. The threshold value for EV plug-in status detection is set to be the average of these two cases.

3.4.1.2. EV premature charging session ending (high temperature problems)

EV premature charging session ending have been reported by the EV users this year, especially when there are four EVs are charging at the same time in hot weather. The premature charging sessions are caused by the protection mechanism when the controller is unable to detect pilot signals with small duty cycle. When four EVs are charging at the same time, their pilot signals drop down to 12% for low power charging. The A/D conversion values of the low pass filtered pilot signals remain low at this situation. Meanwhile,

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all the 8 relays inside the controller box are turned on. As a consequence, the temperature of the controller box increases rapidly. Unfortunately, the amplification ratio of the amplifiers in the pilot signal monitoring circuit drops when ambient temperature inside the controller box increases. In order to protect EV users from remaining power at the outlet when unplugging the handle, the controller should terminate the charging sessions when the pilot signals are not detectable. However, the protection mechanism causes premature charging sessions when four EVs are charging at the same time in hot weather.

In order to prevent premature charging sessions while satisfying the safety requirements, an extra circuit board are added to existing controller to separate the EV detection and EV charging monitoring function. This way, the amplification ratio of the pilot signal monitoring circuit will be increased from 0.33 to 1.2, thereby resolving the premature ending charging issue. Further tests will be performed when ambient temperature becomes high.

3.4.2. Test of GFCI

In order to measure the trigger level and delay of the GFCI circuit, UCLA SERMC has designed a circuit and setup for experiment with the schematics shown in Figure 46 and Figure 47.

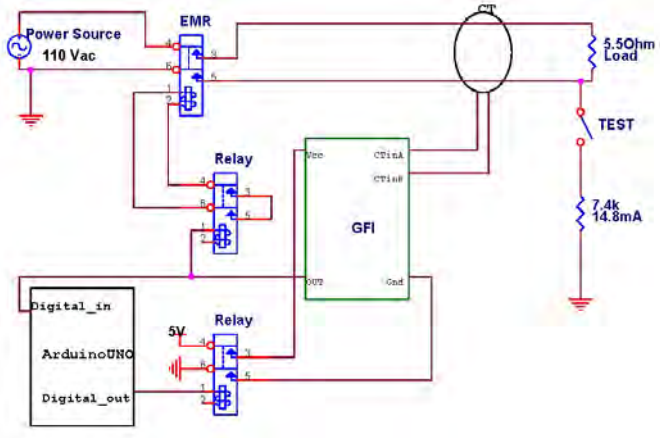


Figure 46. Schematics of GFCI test

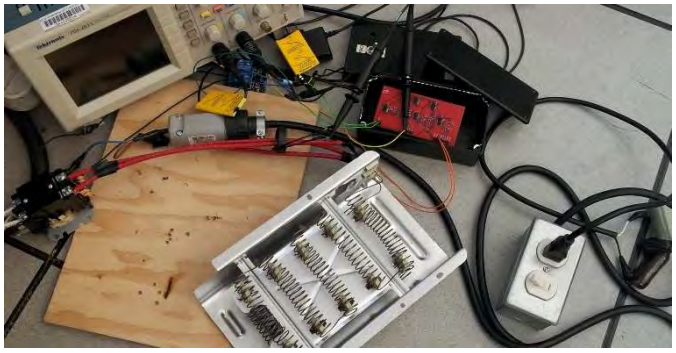


Figure 47. Setup of experiment on GFCI circuit

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In order to see the trigger level and delay time, instead of flipping the TEST switch, which will cause a larger signal to trigger the circuit, the experiment procedure is as follows: (1) TEST switch ON; (2) GFCI is ON; (3) Relay, SW2 is ON. Figure 48 shows the result of the experiment.

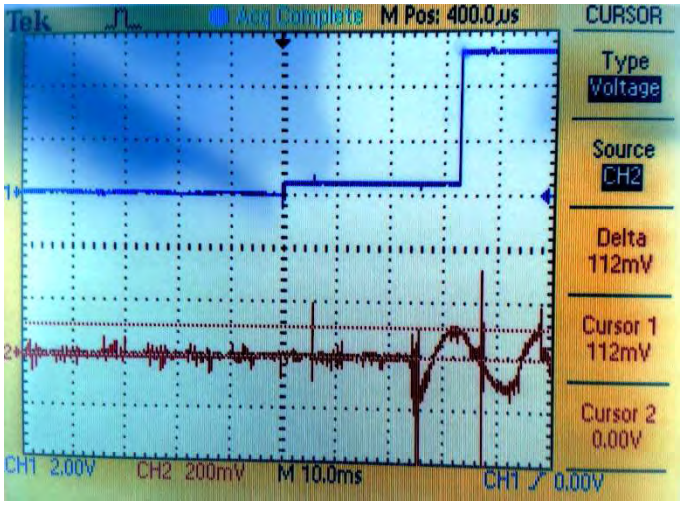


Figure 48. Result of GFCI test

Channel 1 (Blue) is the GFCI trigger signal, and channel 2 (Red) is the output of Current Transformer (CT). The result shows that the SW2 has approximately 25ms delay after GFCI is ON. When there is 14mA difference between the hot wires (which is 110mV here according to the specification of CT), the GFCI triggers on the positive cycle. The results also show that the GFCI circuits has approximately 1ms delay. The GFCI needs to be enclosed in a grounded metal surface box in order to negate the magnetic disturbance from the electromagnetic relay. The GFCI only works for positive cycle of the AC. If an abnormal diversion of current from a hot wire happens on the negative cycle, the GFCI trigger will be delayed by 8.33ms. The GFCI was tested at least 300 times on each of four channels with no failure. These tests were done with 21A load current, channel by channel.

The layout of the GFCI circuit board has 4 layers with two inner layers for the VCC and ground. This design allows us to mitigate false alarms from electro-magnetic waves by enabling us to turn the relay on/off. The GFCI circuit is tested before the charging process begins. The controller emulates the GFCI triggering signal to the CT by turning on/off a Darlington transistor with a 330 ohm/1 watt resistor hooking on dc 12V. If the GFCI circuit does not pass the testing process, the controller will stop the charging process and return a GFCI error to the server.

The GFCI detection during the charging process is implemented by using an interrupt of the controller so that the charging process can stop immediately when the ground fault happens. The GFCI circuit is reset when the EV use unplug the EV so that the next EV user is able to start charging process. Note that there is a 500 us delay in the interrupt process due to the false alarm issue.

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3.4.3. Voltage Detector

We added a voltage detector as a safety feature to our level 2 smart EVSE that can monitor the output of the relay to find possible electric leakages or relay welding that sometimes happens on electric contactors. The voltage detector is connected to each relay output in the smart EVSE, and keeps reading the voltage of the output. If it detects an undesired voltage on the relay output, the voltage detector will send a signal to the controller to trigger the related safety process that is written in the firmware (e.g. stop charging station or report problems). Figure 49 shows the schematic design of the voltage detector.

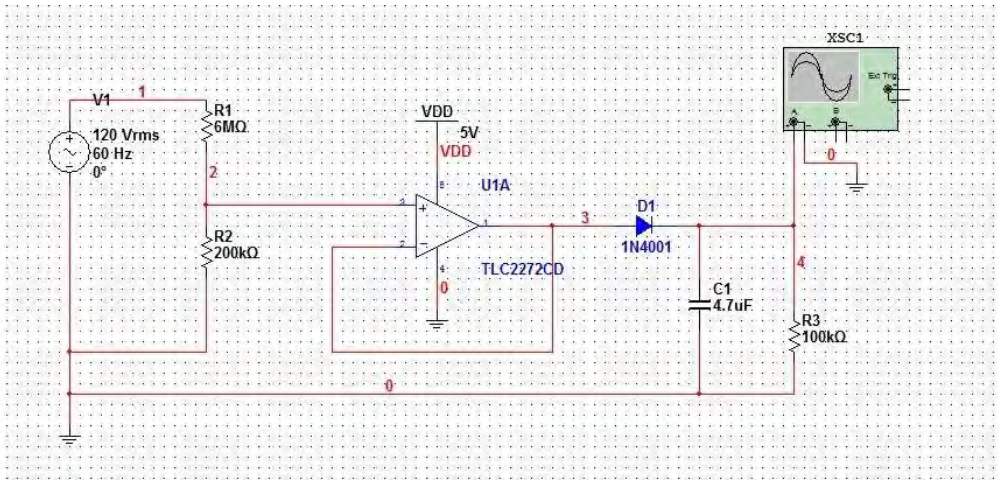


Figure 49. Schematic of voltage detector

The voltage detector directly connects to the output of the relay, and then a 31:1 voltage divider follows the input to lower the input voltage from 110V to 3.5V. The 3.5V input goes into an op-amp that functions as a voltage follower. The op-amp is used to isolate the high voltage part, which is connected to the relay output, and the low voltage part, which is connected to the charging control electronics. The output of the voltage follower connects to a half-wave rectifier, which consists of a diode, capacitor and resistor. The diode removes negative voltage input, while the capacitor and resistor pair can tune the alternate current sinusoid wave closed to a DC signal. This DC signal is the indicator of the relay output's voltage status and will go into the microprocessor in the charging control electronics for decision-making. When there is no charging activity, the output voltage of voltage detector should stay low. Figure 50 shows the output of the voltage detector when charging is enabled.

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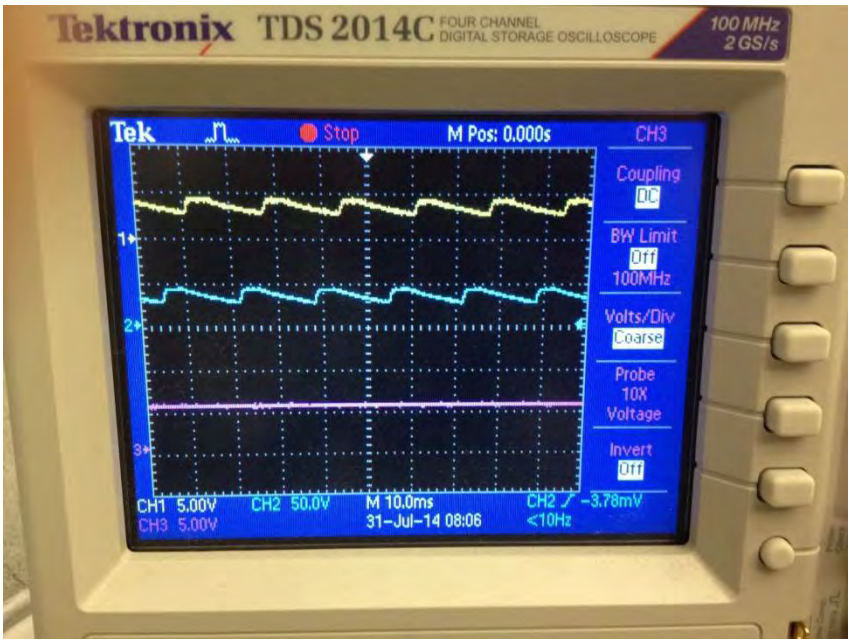


Figure 50. Oscilloscope image of voltage detector output

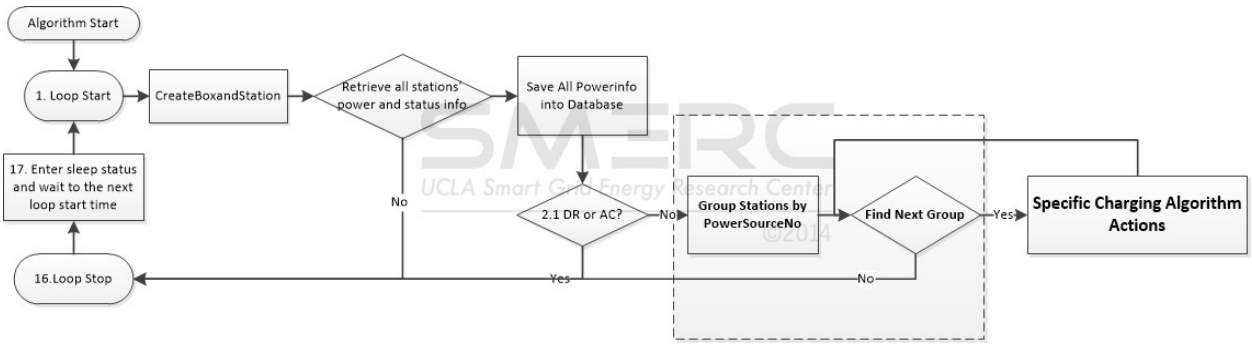
In the firmware implementation, the voltage detection function is inserted into the beginning of the charging initialization process. If the voltage detector detects voltage at the output of the relay when the relay is turned off, the charging initialization process will stop and return relay welding status to the server. When the EV is charging, the voltage detector continuously detects voltage at the output of the relay. If the voltage detector cannot detect the voltage when the EV is charging, the controller will stop the charging process and return a voltage detection error to the server.

3.5. Smart Charging Algorithms

The Control Center offers several algorithms to govern the charging function of an EVSmartPlug™. The following section describes the updates and algorithms in development for SMERC EVSEs.

3.5.1. Code to handle any combination of power sources and stations

API 2.0 includes code to solve the situation when an EVSE has multiple power sources and can handle any possible combination of power sources and stations (charge plugs). In the beginning of each control loop, the charging algorithm will check the associations between charging stations and power-sources, and then logically group them, based on the specific actions the charging algorithms can perform.



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Figure 51. Control loop to handle any combination of power sources and stations

3.5.2. Automated Round-Robin

This algorithm runs on the server side and is used for EV energy scheduling on level 1 EVSEs. Multiple power sources for each EVSE are also supported (e.g. one station must only be connected to one power source of that EVSE, but each power source can support multiple charging outlets). In addition, only one active EV charging session is allowed at the same time.

To illustrate the scheduling process, an EVSE, that has four stations and two power sources are used as an example. Station 1 and station 4 share the same power source, i.e. power source #1, while stations 2 and 3 share power source #2. The algorithm can handle any possible combination of stations to power sources. EV users can plug their EVs into any available stations and the algorithm will start the charging automatically. The algorithm will group the EVSE's stations by their power source(s) and sort every group's station(s) by the station's name or ID. Each power source must be associated with a station group that may have multiple charging stations. Therefore, the number of power sources in the EVSE must be equivalent to the number of station groups.

Once vehicles are plugged into specific charging stations, the algorithm will detect the corresponding station group and the power source. Based on the number of total active charging session on that power source, the algorithm will compute an average switch time for each user. For example, if the time quantum is set to 1 hour, and the number of total active charging sessions is 4, then the average switch time calculated as 60 min/5=15 min. Thus, the power consumption is switched among connected vehicles.

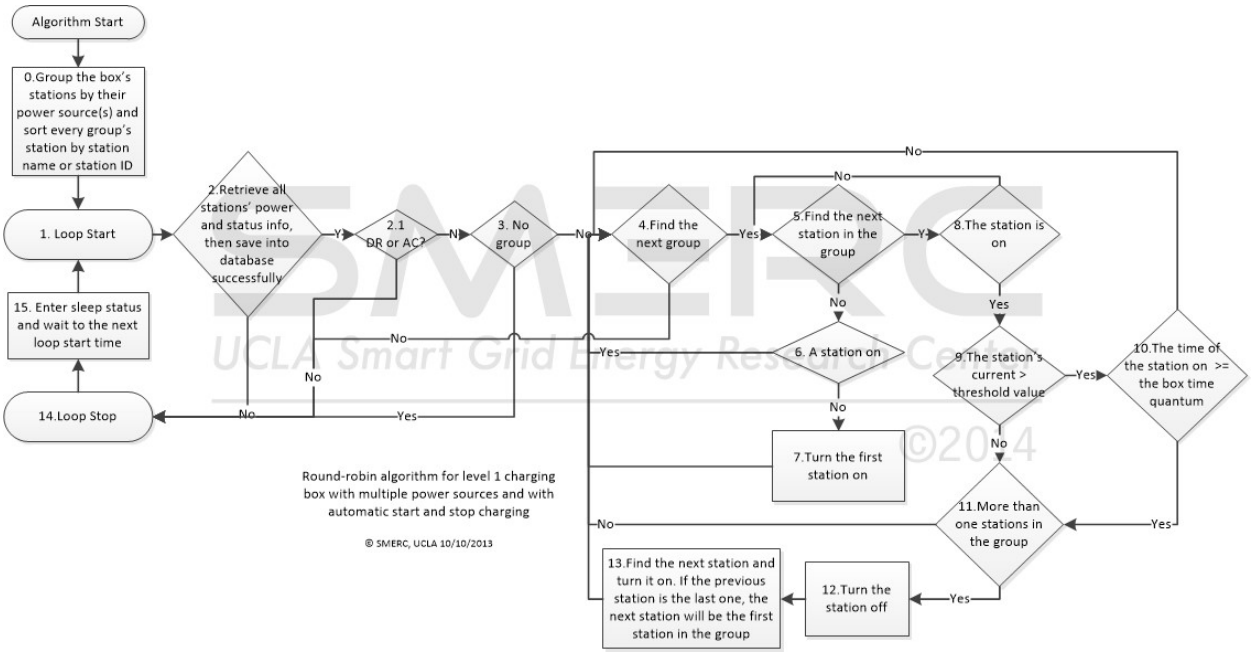


Figure 52. Overview of Automated Round-Robin algorithm

3.5.3. Smart Round-Robin

This algorithm is similar to the previous Automated Round-Robin algorithm except that it is used in cases when EV users must submit a charging request.

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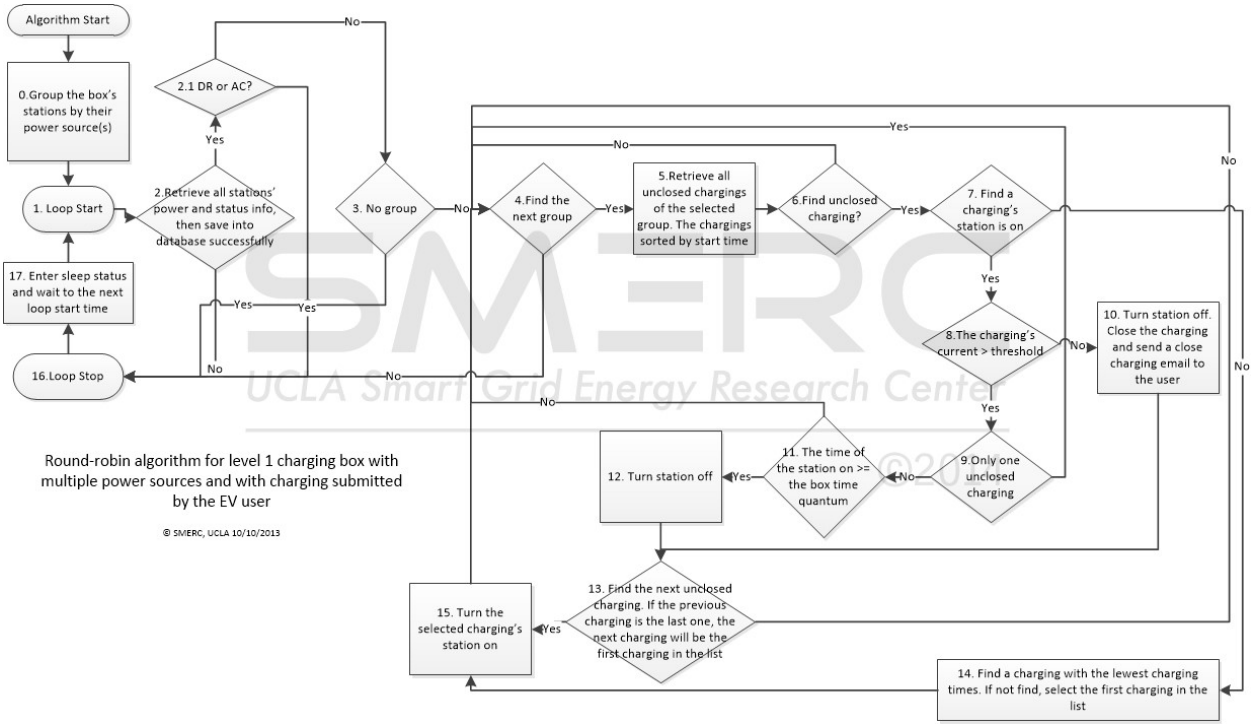


Figure 53. Overview of Smart Round-Robin algorithm

3.5.4. Price Based Charging Algorithm Implementation

We implemented a price-based charging algorithm on the WINSmartEV platform to provide grid regulation services and save charging costs for EV users. A server-side optimization program manages the charging behaviors according to each user's price preferences, daily traveling schedules, and availability of energy supply. The system comprises three main components: Mobile App, retrieval program for energy prices, and scheduling algorithms based on API 2.0 (Figure 54).

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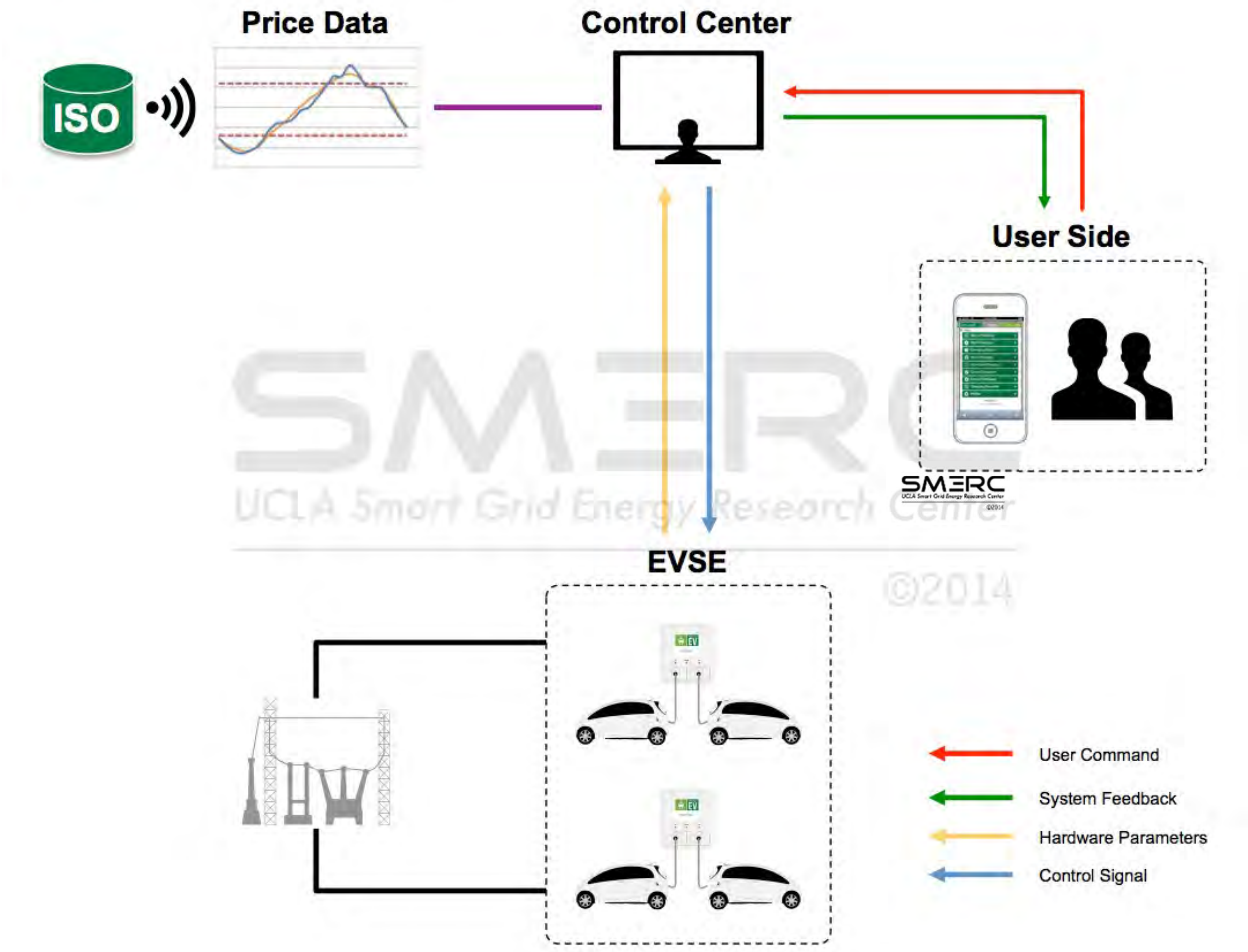


Figure 54. Overview of the Price-Based Charging system

The charging system uses two kinds of price signals: real-time energy prices retrieved one day ahead from CAISO (California Independent System Operator) (Please see section 3.5.4.2 in this report about CAISO price retrieval) and the organizational price signals, which are generated dynamically by our system that account for predicted EV energy consumption and operational costs. Our control center can broadcast both price signals to users' mobile apps. In the implementation scenarios, users submit their charging preferences and schedules through their mobile right after they plug in their EVs. They can select their price preference, i.e. the maximum accepted energy price, and the estimated departing time of the day. Once the information is complete, the predicted energy consumption will be computed on the server side and returned to the mobile App. The charging session will start if users agree with the energy allocation decision. As a core component to this algorithm implementation, a price-based scheduling algorithm on the server side performs the following tasks: 1) Dynamically generates price signals based on grid prices and organizational prices; 2) Retrieves and processes historical charging data, and makes predictions for EV user energy consumption; 3) Computes optimal charging schedules based on charging preferences; 4) Communicates and controls corresponding charging stations.

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3.5.4.1. Existing Smart Charging Algorithms

3.5.4.1.1. V2G Technology and Grid Regulation

Unregulated EV charging behavior could potentially cause instability and damage to the power grid due to new peak loads and intermittency. When the grid load increases, the quality of electricity will drop, i.e. the voltage and frequency, which are both significant for electricity consumers.

The V2G concept was proposed nearly 10 years ago, with the first introduction and implementation conducted by Dr. Willett Kempton [8]. This technology manages EVs and Plug-in Hybrid EVs as power sources for the electric grid. A team at the University of Delaware implemented the V2G technology with the goal to level the grid load during the day; i.e. pull energy out from the EV/PEV batteries and infuse it into the grid when the system load is high or there is a lack of high quality renewable energy supply. When the grid load is low, cars are scheduled to charge their batteries, which is the so-called "valley filling" charging scheme. Based on these developments in industry technologies, an intelligent scheduling algorithm is needed to regulate aggregated EV charging behaviors in order to maintain system stability.

3.5.4.1.2. Centralized Smart Charging

For integrating EV batteries into the electricity grid, previous research work has been done by many scholars, including theoretical modeling and simulations. Generally speaking, their contributions to the scheduling algorithm for smart charging can be divided into two categories: centralized and decentralized algorithms. As a representative of a centralized scheduling algorithm, Han et al. [9] designed an aggregator which works between the grid and EVs to regulate a number of EV's charging schedules by formulating the EV driver's revenue and cost. Taking account of the real time pricing and the infrastructure constraints, the algorithm is capable of calculating the optimal charging schedules, aiming to increase the maximum revenue for users. There is not any indication of how this algorithm can support grid regulation and ancillary services, even though the authors' modeling strategy is applicable with dynamic programming. The authors assume the charging processes of all EVs are static, which does not include the stochastic arrival and departure times of vehicles.

3.5.4.1.3. Decentralized Smart Charging

With electricity price from DAM (day-ahead market), Saber et al. [10] adopt the PSO (particle Swarm Optimization) method to model the EV scheduling problem with V2G option. The objective of a control center is to maximize the user's profit by regulating a number of the EVs' charging and discharging schedules with consideration of battery degradation and efficiency. Hutson et al. [11] improves this approach by defining buy energy, sell energy and hold as three states represented by 1, 0 and -1. Velocities of different particles (EVs) change due to the real time price information and their positions are always changing due to the velocities. The final positions (charging and discharging schedules) of EVs indicate the minimum cost achieved for every EV in the charging schedules. Also, static assumption without stochastic arrival and departure make this algorithm difficult to use in a real world implementation.

Some researchers extend the research with decentralized charging algorithms. Lund et al. [12] use the simulation tool EnergyPLAN to create energy system models including different levels of EV fleets and wind power. Historical travel data is obtained from the U.S. Department of Transportation to model users' travel

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and charging behaviors, based on which smart charging function, including V2G, is applied in the system. The simulation results show integration of regulated EV charging/discharging combined with V2G not only increases the penetration level of sustainable energy, such as wind power, but reduces the green gas emission. Lund's work is inspiring in that historical data of EV user schedules and transportation data can be utilized to formulate a stochastic model to predict user behaviors. However, without V2G inclusion, this algorithm loses much ability to provide grid regulation and ancillary services.

Without a V2G option, Vytelingum et al. [13] utilize an agent-based approach to simulate a human being's learning process. In his algorithm, every EV battery is regarded as an agent, who has self-consciousness to learn gradually to adapt to the pricing policy of energy storage. Based on the day-ahead electricity price, agents change their charging schedules, taking account of battery capacity, battery degradation and daily schedules. This interactive learning process is realistic and quite similar to human learning behaviors, which strengthens the validity of simulation results. However, even though this method may provide more accurate results, the learning process takes longer than the reaction time of grid to load change, which is the main disadvantage of this charging algorithm.

Andersson et al. [14] designs a framework model which implements decentralized charging algorithms with V2G integration to analyze the ancillary service effects of regulated EV charging to short-term imbalance effects of the grids in Sweden and Denmark. EV drivers can decide whether it is time to charge or discharge their vehicles based on their daily schedules. Even though, smart scheduling can achieve maximum profit for EV drivers, according to Andersson, there exists grid insecurity with short-term imbalance when applying V2G, which is worth researching on the topic of V2G control.

For grid regulation purposes, Ota et al. [15] propose a control scheme to control distributed energy storage devices (EV batteries) for a ubiquitous power grid in Japan. Charging or discharging operations depend on grid frequency and SOC of the EV battery. When plugging new loads into the grid, frequency drops and there exists a need for V2G service. Meanwhile, the second control criterion is SOC in the EV battery. Ota does not include price factors into the smart charging algorithm and does not implement his algorithm with real hardware and software systems, even though he has some experimental data to support his idea.

Low et al. [16] from Caltech propose a decentralized algorithm to regulate aggregated EV charging behaviors with the goal to shave the load curve, i.e. valley filling. The author generates notions and standards to describe charging profiles under his modeling method in every time interval, which is modeled as time slots. By enabling the load side participation, this algorithm allows EV drivers to arrive and depart as they want, while providing control charging signals. Finally, the authors study a case where there are twenty EVs in one hundred households to demonstrate the algorithm's functionality. Low's work gives a clear definition of charging profiles and system formulation including objective/constraints and convergent criterion. However, even though the EV users can change their schedules, the revenue is not considered in the algorithm design, which is critical for this algorithm to be implemented in a real commercial system.

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3.5.4.2. CAISO Price Retrieving

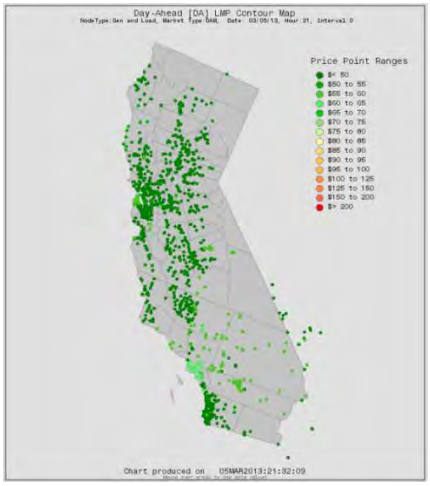


Figure 55. Distribution of transaction nodes in California

As shown in Figure 55, there are more than 500 nodes in California to monitor electricity wholesale prices based on bidding policy. Currently, CAISO operates day-ahead, hour-ahead, and real time electricity markets by managing congestion, ancillary services, and a balancing program for the system in every transaction node. On the CAISO website, supply and demand information is updated in real time, while the local marginal price (LMP) and other types of prices in different nodes are updated every 5 minutes in the Open Access Same-time Information System (OASIS). Figure 56 shows sample information from the OASIS website.

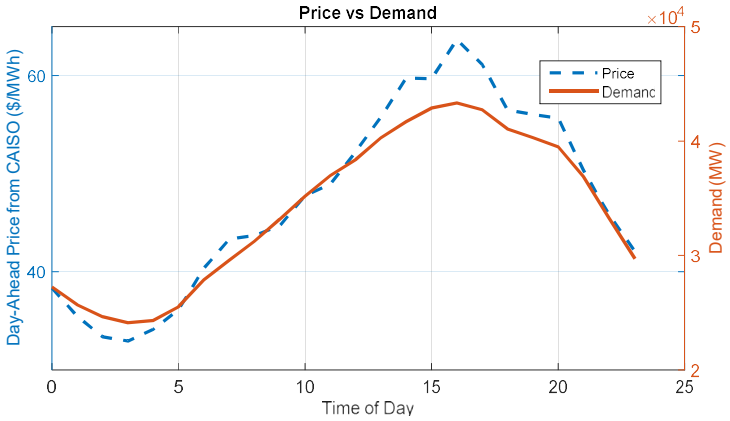


Figure 56. A sample of Price vs Demand from CAISO

Two different electricity markets are useful to this project and their data will be retrieved from the CAISO web interface: day-ahead and real-time prices. Day-Ahead Market is a forward market in which hourly LMPs are calculated for the next operating day based on generation offers, demand bids, and scheduled bilateral transactions. Real Time Market is the real time electricity price monitored and projected by CAISO which gives instant information about the electricity market. In this case, the interval is set at 5 minutes. The fluctuation of real time prices reflects the fluctuation of the grid's load.

In this project, we utilized a Windows service program running on the EV server to download the prices from day-ahead market (DAM), Hour-ahead Market (HAM) and Real-time Market (RTM). DAM prices were

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retrieved and stored in database every 24 hours, HAM every hour and RTM every 5 minutes. However, the CAISO price retrieval interface, which is an http link to specify the market, time interval and node information, was updated on 2015-02-06 and the access interface has been closed. The price data from 2013-10-09 to 2015-02-06 for different markets is still in our EV database and are used as a reference as needed in this project.

3.5.4.3. Validity for Price as a Signal

According to the CAISO market standard, local marginal prices represent the efforts of electric utilities to manage the grid, which includes the voltage and regulation of frequency profiles and management of intermittency. Once the difference between demand and generation increases, the regulation cost will increase accordingly because demand exceeds generation. In this case, the operator has to invoke the backup generators (usually instant reacting generators like diesel generators with associated high costs) to supply electricity. On the contrary, if there is surplus supply in the grid, utilities also have to pay the transmission and congestion cost, which happens in very few cases. Therefore, based on the market mechanism, prices reflect the grid's load and imbalances. If the price goes up, the demand is high and methods should be taken to mitigate the load imbalance. As is shown in Figure 56, the load tracking property for real time prices is obvious, especially in the demand peak and valley periods. The proposed pricing schemes for implementation should preserve the nature of this property and reflect the imbalance between demand and supply.

3.5.4.4. Pricing Policy

The purpose of designing an appropriate pricing strategy is to encourage EV users to shift their EV charging load to a preferable time range. Since charging facilities are installed in a university campus, charging behaviors are believed to have similar patterns in terms of arrival times, departure times, and energy, as required by faculty and students. It is assumed that varied persons may have different reactions towards price options; e.g. for a certain day, 20% of all customers are willing to pay the highest prices to charge enough energy as soon as possible. Another assumption is that electricity price is linearly related to system-wide load/demand; i.e. price increases as predicted demand increases. Thus, twenty-four prices, one for each hour, are generated a day ahead, by accounting for the predicted EV charging load and the desired load. We have two ways of generating real time price signals, which will be broadcast to EV users. The first one is comparatively simple, based on the wholesale price signals retrieved from CAISO. The second one is an organizational pricing strategy, which combines the prediction of EV load and real-time actual EV load to produce dynamic price signals that represent EV demand and energy supply conditions in the local area. The prices are defined by:

For CAISO Price Signals:

$$P_i = P_b + P_{r_i} + P_{ad_i}$$

P_i denotes charging price in i_{th} hour of current day; P_b denotes the base price for the EVSE selected, which is related to the operational cost; P_{r_i} is the real time price retrieved from CAISO for i_{th} hour; P_{ad_i} denotes the price adjustment for i_{th} hour, according to system management requirements.

For Organizational Price:

$$P_i = P_b + \alpha(L_{pi} - L_{di})$$

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P_i denotes charging price in i_{th} hour of current day; P_b denotes the base price for the EVSE selected, which is related to the operational cost; L_{pi} is predicted load value for i_{th} hour; L_{di} denotes the desired load value for i_{th} hour. α is a coefficient defined to reflect the relationship between load and price. We offer users five price options, from highest to lowest, as a charging threshold; i.e. accepted maximum price. As an example, the charging aggregator can set a maximum value discourage EV users from charging between 1:00 PM and 3:00 PM.

3.5.4.5. Scheduling Algorithm

Each level I EVSE has 4 outlets and only one power source. Meanwhile, only one vehicle is allowed to charge at a time due to the inner circuit's design. Thus, the policy is to determine the timing to switch from one vehicle to another according to users' preferences and priorities. An accepted price threshold is selected before users submit charging, which is assumed to reflect how urgent he/she needs to charge. As a result, a charging session with a higher price has higher priority and is able to consume more energy within every time quantum. The criteria for the algorithm for switching charging sessions is

$$T_i \geq (\mathrm{P}_i / \sum_{i=1}^{n} P_i) \cdot \Delta T = \gamma_i \cdot \Delta T$$

Where T_i is continuous charging time, since the last time of activation; P_i the price selected by i_{th} user; and ΔT is the time quantum, denoting the timespan of EVSE control loop. γ_i is defined as a priority coefficient according to bids provided by users for current the EVSE.

The scenario for a level II EVSE is different, because it has a larger power supply with the ability to multiplex current. The EVSE selected for implementation has a single power source (240V, 30A). Multiple outlets (stations) can charge at the same time, but the current for each outlet should be between 5A (10% duty cycle) to 30A (50% duty cycle). Accordingly, the algorithm will determine the energy sharing policy in a current multiplexing manner. To determine each participating vehicle's charging duty cycle (DC), a two-step process is conducted. The first calculation will rule out the vehicles whose duty cycle values are lower than 10%, and the second calculation reallocates the source current.

$$DC_i = I_{\max} \cdot (\mathrm{P}_i / \sum_{i=1}^{n} P_i) = I_{\max} \cdot \gamma_i$$

γ_i denotes the priority coefficient, which is defined as $\gamma_i = \mathrm{P}_i / \sum_{i=1}^{n} P_i$.

The final cost for participating users consists of the cost for purchasing electricity and the fee for occupying the charging service priority. Thus, the final cost for each user can be expressed in a simple model with electricity price for a specific hour, P_i and the current user's priority ratio, γ_i :

$$C = \sum_{k=k_0}^{k_j} \eta_k \cdot \Delta t \cdot P_k \cdot R_k = \sum_{k=k_0}^{k_j} (1 + \beta \cdot \gamma_k) \cdot \Delta t \cdot P_k \cdot R_k$$

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Where C denotes the final cost; η_i is the cost factor considering priority to occupy power source in k_{th} timeslot. For simplicity, we apply $\eta_k = 1 + \beta \cdot \gamma_k$ to include both the cost for purchasing electricity and priority service fee. β denotes the priority price coefficient and is tentatively set to 0.1 in the experiment. P_k is the price for k_{th} timeslot and R_k is the charging rate in i_{th} timeslot. In both level I and level II charging scenarios, priority coefficient γ_k can be obtained by calculating the ratio of current user's bid among all players connected to the EVSE.

Implemented algorithms on server side are capable of regulating charging sessions with dynamic arrival times, departure times, and varied price preferences. Figure 57 shows the design flow of the simplified versions of the implemented algorithms.

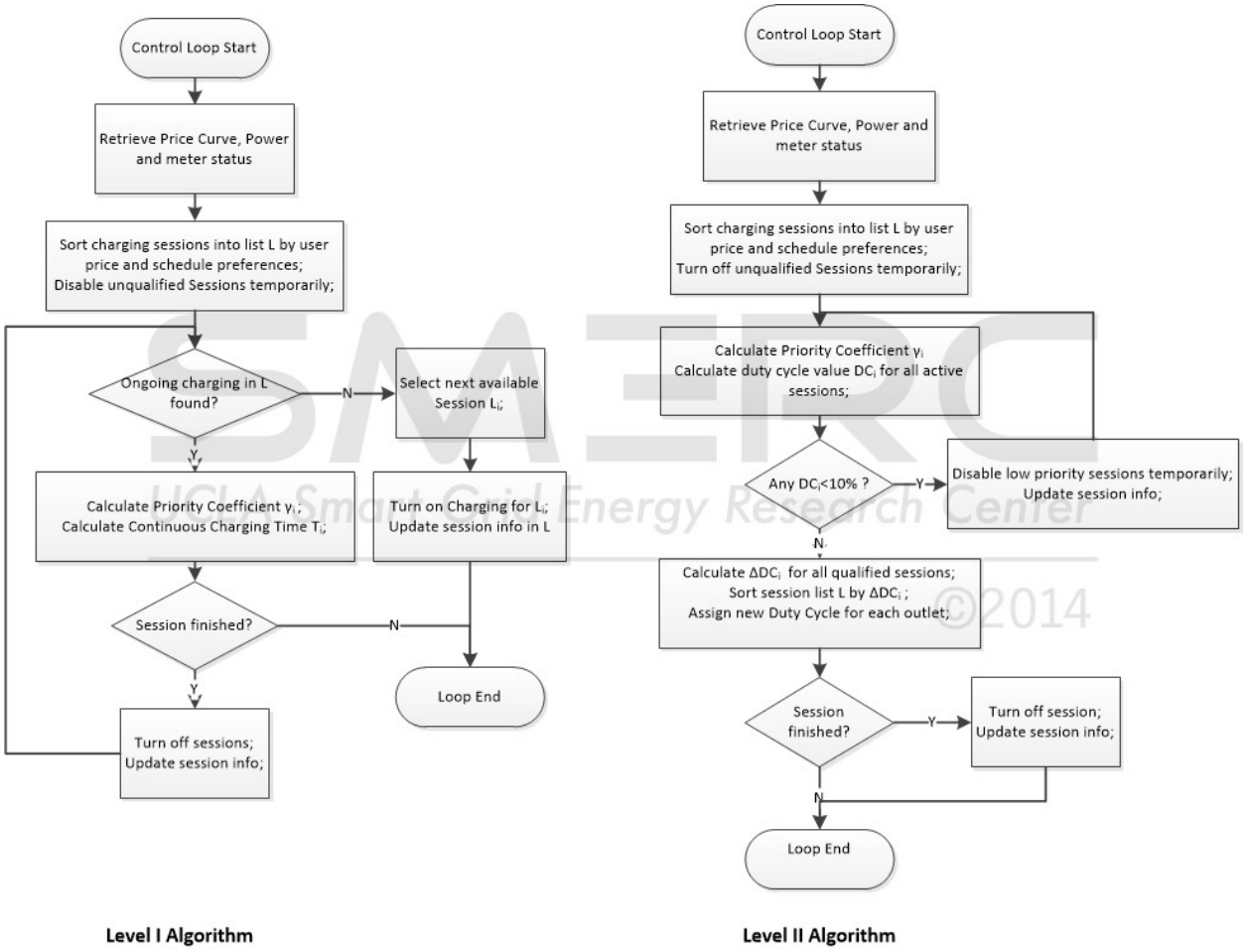


Figure 57. Simplified versions of the implemented algorithms

For level I EVSE, after each control loop starts, the algorithm will select active charging sessions for the current EVSE from the database, and sort them by their accepted prices and departure times. Only the charging sessions whose prices agree with user price preferences can be retrieved. It is assumed that EV drivers with higher accepted prices and earlier departure times have urgent need for energy and will be

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given higher priorities than others. To guarantee the energy assigned among users in each time quantum is proportional to their priorities, the algorithm calculates the priority coefficient γ_i and the continuous charging time T_i in each control loop. If the current charging session has used up its portion of charging time in the current time quantum, the algorithm switches from this charging to a lower one from the charging session list. For level II EVSE, priority coefficients and corresponding duty cycle are calculated in a two-step manner. In the first step, the charging session will temporarily be disabled if the duty cycle calculated is lower than 10% or the user accepted price is lower than the current price. Then, after ruling out the unqualified charging sessions, the algorithm will re-allocate the power source to each remaining session in proportion with its priority coefficient. The charging sessions will be closed if the current is lower than the threshold or the schedule's deadline is reached.

3.5.4.5.1. EV Charging Load Prediction

We average the system-wide charging load on an hourly basis for better prediction. As shown in Figure 58, the system's EV charging loads indicate a periodicity property; i.e. the load has a similar pattern every other week and on each workday except Friday. However, the historical data is imperfect with data missing for certain time intervals and wrong values caused by hardware failure. Thus, we have implemented a data modification method to correct the data series.

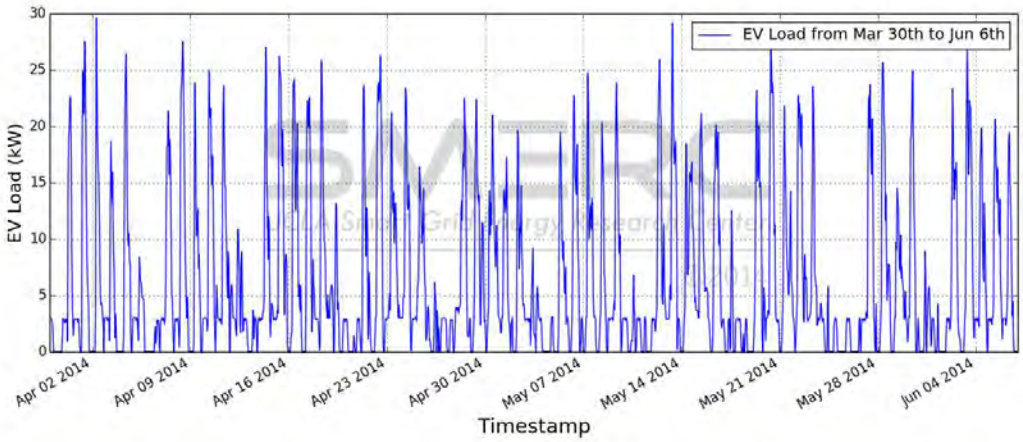


Figure 58. EV charging load indicating a periodocity property

We have selected an autoregressive moving average (ARMA), as a stationary time series model, to model the data and perform prediction. There are two parts to the ARMA model, i.e. autoregressive (AR) with order p, and moving-average (MA) with order q. The general expression is:

$$X_t - \varphi_1 X_{t-1} - \cdots - \varphi_p X_{p-1} = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$$

In the expression, ε_t is white noise with a 0-mean and variance equal to σ_ε^2. The following procedures handle historical charging load records:

i. Error correction and data pre-processing

ii. Determining orders for ARMA model, $i.e.$ p and q

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iii. Model Fit, *i.e.* calculate φ, θ values

iv. Model validation, *i.e.* error analysis

Since the raw data, even after modification, has non-stationary property, differencing steps are necessary to transform them into a stationary time series. The seasonal factor is identified as 168 hours from the plot, equivalent to one week, to remove data periodicity. Additionally, to make the model stable without incremental and decremented trends, Y_t is first-order differentiated with adjacent values in the time series.

$$Y_t = X_t - X_{t-s}$$

$$W_t = \nabla^1 Y_t = Y_t - Y_{t-1}$$

We utilize Akaike and Bayesian Information Criteria (AIC, BIC) to evaluate the selections of model orders. The prediction results are shown in Figure 59.

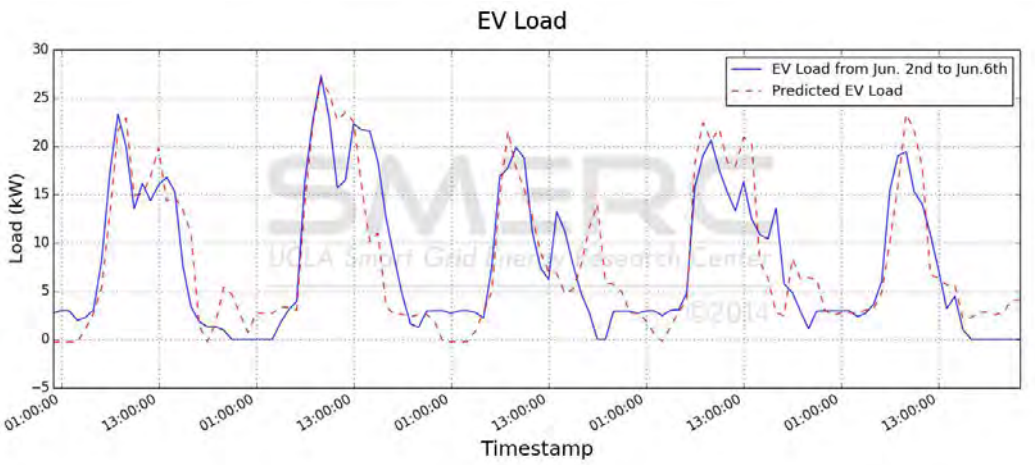


Figure 59. Prediction using the Akaike and Bayesian Information Criteria (AIC, BIC)

3.5.5. Fair Charging Algorithm

The PEV charging infrastructure must take into account external factors – such as energy cost, grid conditions, user preference, local power capacity, etc. – to deal with grid issues and reach target goals. In order for the system to work optimally, these specified issues and targets must be addressed using sophisticated charging algorithms which control the PEV charging automatically either by centralized or decentralized control schemes. These two design schemes guide the implementation of the algorithm: in a centralized control scheme, the control center controls the charging stations, while the controller in the charging station executes its embedded algorithm in the decentralized control scheme.

To maximize use of the available electrical grid and circuit capacity, the charging algorithm either on the server or in the charging stations executes efficient control schemes to fulfill their objectives. In order for this PEV multiplexing charging scheme to become more appealing to users, the fair allocation of energy

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should be maximized by the charging algorithms by providing variable power to several PEVs from one circuit, either through multiplexing or variable current control.

3.5.5.1. User's Stay Hour Prediction

In order to show the accuracy of prediction, we define the error rate of prediction $\varepsilon(T_{Predict})$ in (1)

$$\varepsilon(T_{Predict}) \equiv \frac{\sqrt{(T_{Stay} - T_{Predict})^2}}{Max(T_{Stay}, T_{Predict})} \quad (1)$$

According to the prediction rule introduced in section III, the users' T_{stay} prediction error rate distribution is shown in Figure 60. Note that the first and the second charts use $\mu[\varepsilon(T_{Predict})]$ and $\sigma[\varepsilon(T_{Predict})]$ to represent predictable people, while the third and the forth use $\mu[\varepsilon(T_{Predict})]$ and $\sigma[\varepsilon(T_{Predict})]$ for unpredictable people.

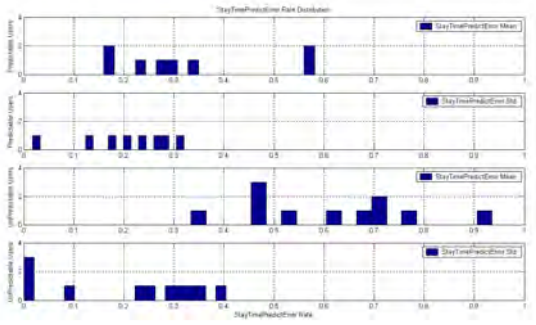


Figure 60. Prediction of error rate distribution

The data shows that the predictable people have better behavior in both $\mu[\varepsilon(T_{Predict})]$ and $\sigma[\varepsilon(T_{Predict})]$.

3.5.5.2. Design of Fair Charging Algorithm

Experimental results of User's Stay Hour Prediction and Fair Charging Algorithm are presented in the following subsections.

The Station Controller of the server-based control system regulates the charging stations based on the charging algorithms. The algorithms can be developed based on user's time, energy price, or energy amount.

For a "fair enough" charging system, each user's charge ratio τ , defined as the ratio of the charging time T_{Charge} and the stay time T_{Stay}, should be close enough to be fair. To be more specific about the fairness system, for a given charging event, every user's mean charge ratio $\mu(\tau)$ should be close to the mean charge ratio of every user charging at the time $\mu[\mu(\tau)]$. Therefore, both $\sigma[\mu(\tau)]$ and $\mu[\sigma(\tau)]$ must

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approach 0 when the system approaches a fair system. The fairness index α is defined in (1) to indicate the fairness of the system.

$$\alpha \equiv 1 - \{\sigma[\mu(\tau)] + \mu[\sigma(\tau)]\}/2 \qquad (1)$$

The round robin algorithm seems fair; however, the fairness index shows that it favors the first user that starts charging. In the fair charging algorithm, when the second user's charging session overlaps that of the first user, the server predicts the second user's charge time and the first user's stay time. After calculating the first user's remaining charge time, the server stops the first user's session and starts the one for the second user. Before the first user leaves, the server switches back to finish the first user's session after finishing a certain portion of the second user's turn. The third user's session is treated as an overlap of the second user, the fourth user's turn is treated as overlap of the third user, and so on.

Fairness could be maximized by continuously switching charging power between EVs. This would be feasible if the time to switch charging sessions between EVs was close to zero. However, the period of time to switch charging from one EV to the next can be in the order of minutes given hardware and network constraints. If the system switched continuously between users, much charge time would be wasted in the switching process, causing all users to be worse off. If the prediction of the user's stay time is accurate, the fairness maximization can be obtained while only switching charging once. Table 3 summarizes the characteristics of three types of predictable and unpredictable people from the charging records.

Table 3. Mean and standard deviation of Stay time

Type	1	2	3
	Predictable		Unpredictable
Relation between T_{Stay} and $T_{CheckIn}$	Independent	Dependent	
Mean: $u(T_{Stay})$	0.11		5.98
STD: $\sigma(T_{Stay})$	0.03		13.38
Correlation: $\gamma[T_{CheckIn}, T_{Stay}]$	0.067	-0.5984	0.0398
Characteristics	$u(T_{Stay}) > \sigma(T_{Stay})$ $\gamma[T_{CheckIn}, T_{Stay}] \approx 0$	Negative Value of $\gamma[T_{CheckIn}, T_{Stay}]$	$u(T_{Stay}) < \sigma(T_{Stay})$ $\gamma[T_{CheckIn}, T_{Stay}] \approx 0$

For predictable people, based on a user's charging records, $u(T_{Stay})$ is used to predict T_{Stay} of type 1 people, while a simple linear regression function is used for type 2 people. For unpredictable people, the average stay time of all users $u[u(T_{Stay})]$ is used for prediction. A number of switches may be required if the prediction of the stay time is not accurate enough. In real world applications, the optimization of the fairness algorithm needs to take into account both the confidence of stay time and the time wasted in switching.

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In the simulation, we use the same Check-In Time in the charging records as the input of the fair charging algorithm. After redistributing the power, the mean and the standard deviation of the ChargeTimeRatio τ are calculated in Table 4.

Table 4. Comparison between $\tau_{RoundRobi}$ and τ_{Fair}

Charging Algorithm	$\mu[\tau]$	$\sigma[\tau]$
RoundRobin	0.6014	0.5561
Fair	0.7281	0.2329

From the simulation results, the increase of $\mu[\tau]$ and the decrease of $\sigma[\tau]$ mean that the users get energy more evenly from the charging station. To see how the system treats each user, the ChargeTimeRatio τ of each user are separately accumulated. The distribution of $\mu[\tau]$ and $\sigma[\tau]$ of each user is shown in Figure 61.

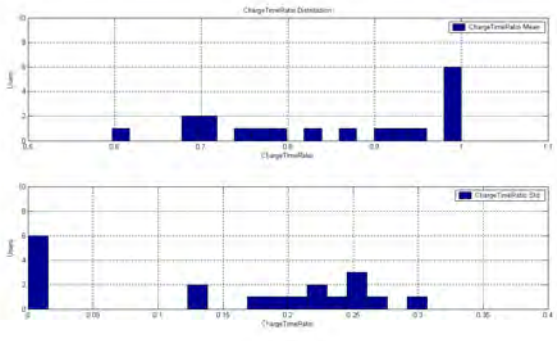


Figure 61. New ChargeTime Ratio Distribution

The parameters of Fairness and Convergence are summarized in Table 5.

Table 5 - Fairness Comparison

Index	Parameter	Charging Algorithm	
		Round-Robin	Fair
Charge Ratio Average	$\mu[\mu(\tau)]$	0.5770	0.8492
Fairness Condiction 1	$\sigma[\mu(\tau)]$	0.2345	0.1374
Fairness Condiction 2	$\mu[\sigma(\tau)]$	0.2649	0.1509
Convergence	$\sigma[\sigma(\tau)]$	0.4018	0.1138
Fairness	α	0.7503	0.8558

The results show that the Fair Charging Algorithm is fairer to the users compared with the round-robin algorithm.

3.5.5.3. Design of Fast Response Infrastructure

In this section, the distributions of round trip time of power information retrieval are measured and presented. The round trip time of power information retrieval corresponds to the waiting time of the server for the response from the charging station after sending out the power information retrieval command. The round trip time, $T_{RoundTrip}$, is expressed in (2):

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$$T_{RoundTrip} = T_{Network} + T_{Metering}$$
$$= \left(T_{Server_Cloud} + T_{Cloud} + T_{Cloud_Station}\right) + T_{Metering} \quad (2)$$

$T_{Metering}$ stands for the time required by the meter in retrieving the power information and it is roughly estimated in the experiments. $T_{Network}$ includes the time required between the server and the charging station. The charging station can connect to the internet through different networks including Ethernet, WiFi, and 3G, which makes $T_{Cloud_Station}$ the dominant factor in the round trip time of power information between the server and the charging station, $T_{RoundTrip}$. Figure 62 shows the distribution of the round trip times. The round trip times were recorded every 5 minutes in one week under different network configurations. The upper chart is with Ethernet while the lower chart is with WiFi. Here we use $T_{Ethernet}$ and T_{WiFi} for $T_{Cloud_Station}$ in these two cases. Note that the server and the charging station are under the same default gateway in the experiment.

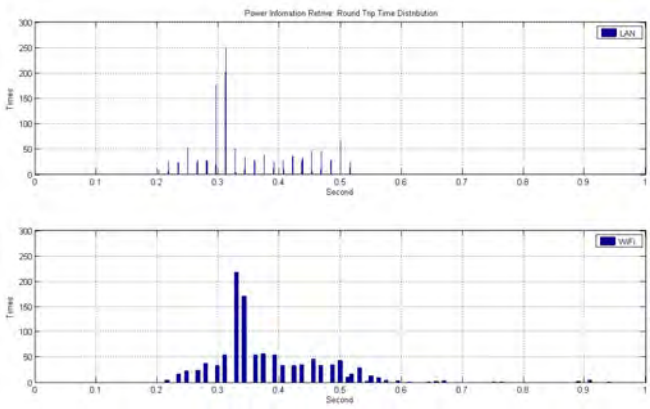


Figure 62. $T_{RoundTrip}$ with Ethernet(Upper) and WiFi(Lower)

The experiment shows that the shortest $T_{RoundTrip}$ is around 0.2 seconds. Normally, when the server and the charging station are under the same default gateway with Ethernet, the $T_{Ethernet}$ is within the microsecond degree, which could be neglected in $T_{RoundTrip}$. T_{Cloud} is also approximate to 0 in this case; therefore, $T_{RoundTrip}$ will be approximate to $T_{Meterging}$, which is expressed in (3):

$$T_{RoundTrip_Ethernet} = \left(T_{Ethernet} + T_{Cloud}\right) + T_{Metering} \approx T_{Metering} \quad (3)$$

Here, $T_{Metering}$ is the dominant factor in the Ethernet case; therefore, the distribution of $T_{Metering}$ is approximate to $T_{RoundTrip}$ in the Ethernet case. Comparing with the Ethernet case, the lower chart of Figure 62shows that T_{WiFi} is slightly slower than $T_{Ethernet}$. Note that $T_{Metering}$ is still the dominant factor in WiFi case.

As for the 3G case, $T_{RoundTrip}$ distributions of 3 charging stations in different locations: UCLA, LA downtown, and Santa Monica are measured in second, third, fourth charts in Figure 63. The first chart is the Ethernet case for comparison.

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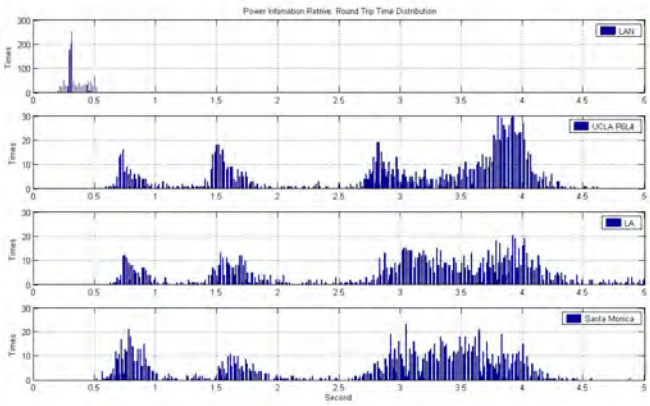


Figure 63. $T_{RoundTrip}$ with 3G in 3 different locations

The round trip time $T_{RoundTrip}$ of 3G cases can be expressed in (4):

$$T_{RoundTrip_3G} = \left(T_{Server_Cloud} + T_{Cloud} + T_{3G}\right) + T_{Metering} \approx T_{3G} + T_{Metering} \quad (4)$$

The experiments show that T_{3G} is not a constant offset from the Ethernet case, but a distribution probability with four peaks measured in its distribution. The distribution of round trip time in 3G cases, $T_{RoundTrip_3G}$, shows no apparent difference in different locations; therefore, the round trip time model could be used in other places as long as they have the same configuration.

Considering that T_{3G} could be time variant during the day and the week, Figure 64 shows $T_{RoundTrip_3G}$ during the week and the days of the charging station at UCLA. The first chart is $T_{RoundTrip_3G}$ during a week and the x-axis of first chart stands for seven days (0 to 1 is Sunday, 1 to 2 is Monday, etc.). The second and the third charts are the $T_{RoundTrip_3G}$ on Sunday and Monday.

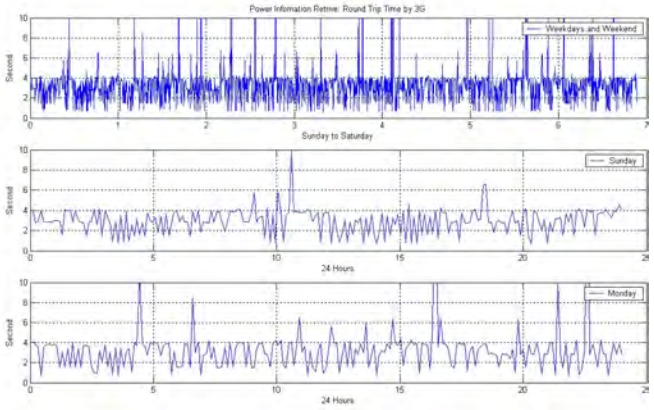


Figure 64. $T_{RoundTrip_3G}$ during the week and the day.

The results show that $T_{RoundTrip_3G}$ are faster during certain hours of Sunday and Monday, but the range of the distribution is no different in these two cases.

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3.5.6. Remote or Local Charging Algorithm

Charging algorithms with power information retrieval can be implemented locally in the charging station. The system with embedded charging algorithms, in which the traffic between the charging station and control center is reduced, is faster than that with remote charging algorithms which are implemented on the server. However, from the experiment's results, the Fair Current Sharing Algorithm performs better than the Simple Current Sharing Algorithm with more user information. Because the Fair Current Sharing Algorithm is based on the user's historical charging records, it is proper to implement it on the server. With the charging stations equipped with power information collectors (PICs) set for data pushing mode, the Fair Current Sharing Algorithm is more practical due to the improved response time of the system caused by the PIC.

Nevertheless, it is also possible to obtain the user's stay time, if the user's EV is equipped with the VMM, which facilitates using the battery's state of charging (SOC) to predict the user's stay time. In this way, it is possible to implement the Fair Current Sharing Algorithm in the charging station.

3.5.7. Event-based Smart Charging Algorithm considering uncertainty of user behaviors

Uncontrolled Electric Vehicle (EV) and Plug-in Hybrid Electric Vehicle (PHEV) charging within a local distribution grid may cause unexpected high load, which further results in power quality degradation. However, coordinating charging behaviors of a number of EVs is a challenging task, which involves not only the deterministic schedule computing but also nondeterministic EV driver behaviors with random arrival time and energy demands. Previous researches in this area rarely consider these random behaviors for real EV users. In this section, we will discuss an implementable event-based cost optimal scheduling algorithm (ECSA), which solves EV scheduling problem by dynamically estimating the stay duration and energy demand for each participating EV user. Datasets, including users' historical charging records and time series meter data collected from Electric Vehicle Supply Equipments (EVSEs) on UCLA campus, are utilized for feature extraction. Based on that, proper inference technique from time series data is employed to determine parameters within each charging session. In addition, solar generation integration into EVSEs is also considered in our problem formulation. The proposed approaches are tested and validated by real EV charging schedules of uses in UCLA campus. The results from simulation experiment demonstrate that the proposed algorithm has a better performance in cost minimization and load shifting compared to existing equal-sharing scheduling algorithm (ESSA).

In this section, we elaborate the implementable solutions to handle the dynamical and random charging behaviors. The objective is to minimize the operational cost for charging services and satisfy charging demands to maximum extent. Renewable energy resources are modeled as the potential power supply for existing EVSEs. The scheduling algorithms will be triggered once pre-defined events are detected by monitoring program. The contributions of this scheduling algorithm can be summarized as: 1) Proper inference is utilized to determine parameters for EV charging sessions， based on the real time usage data collected in more than 50 EVSEs with more than 200 charging outlets in UCLA campus; 2)We consider the EV charging schedules from real users in UCLA campus and develop algorithms to adaptively estimate charging session parameters, such as energy consumption and stay duration. 3)Event-based scheduling

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algorithm is developed to handle random EV charging behaviors by analyzing users' historical records and then adaptively update schedules to minimize the operational cost and maximize the utilization of renewable energy.

3.5.7.1. Proposed System Architecture

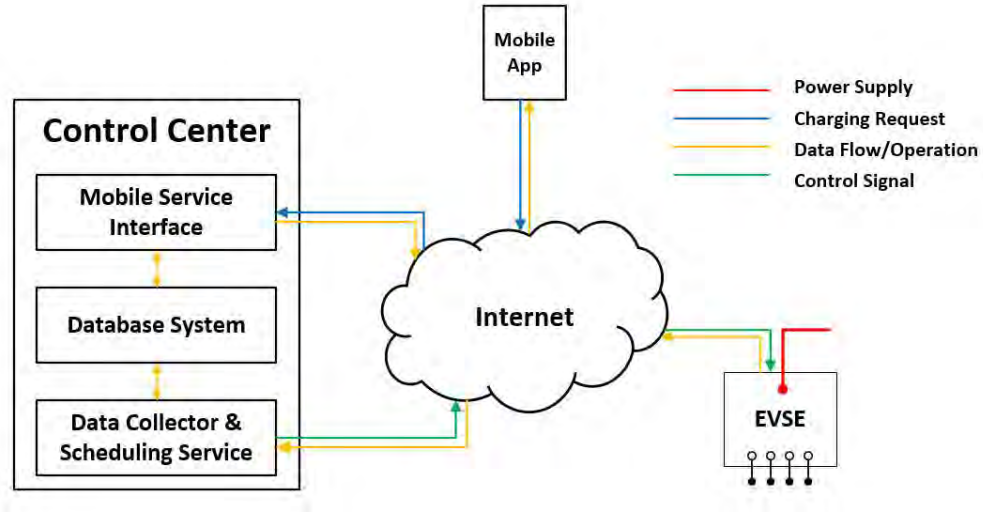


Figure 65 System Overview

System architecture and functioning components are displayed in Figure 65. Charging services on software side are built on top of the complex communication network among numerous components in the system, including EVSE, EV users and cloud side services. On client side, EV users are able to initiate a charging session by sending charging requests through their mobile applications. Immediately, the corresponding EVSE information and user account ID will be pushed to mobile service interface on control center via secured HTTP message. Meanwhile, another service with both data collection and scheduling modules are running on control center, which periodically retrieves real-time data from meters in each EVSE. Once pre-defined events are detected by the monitoring program, corresponding scheduling algorithm will be initiated to handle the charging sessions on that specific EVSE. All the monitoring data in time series for each EVSE and records for all charging requests associated with user information are stored in database system, which can be later accessed by other services, such as feature extraction service. As a possible implementation in the future, the power source for each EVSE can be connected to both grid and renewable generations, e.g. solar panels, in stand-alone mode.

3.5.7.2. Data Analysis for EV charging behaviors

In this section, we briefly introduce the methods we use to extract important features from raw data and further estimate schedule parameters given start time and user index. The dataset that is used in this section contains more than 10000 valid charging session records since 2013 Jan. 1st. There are more than 200 active users, more than 50 EVSEs and 200 charging outlets in this system.

- Parameters to Describe a Charging Session

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To evaluate impacts on electric grid from EV charging behaviors, the following parameters can be defined to describe EV charging sessions. Figure 66 illustrates sequence of parameters in time series.

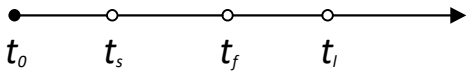


Figure 66 Charging session Parameters

- *Start Time*: t_s, represents the time when vehicle arrives at certain EVSE and submits a charging request.
- *Finish Time*: t_f, denotes the time when this charging session is terminated due to low charging current, which might be caused by fully charged battery or disconnected vehicle.
- *Leave Time:* t_l, is the time when the user unplugs her vehicle and leaves charging infrastructure directly.
- *Charging Power*: $r_n = \{r_{t_s}, r_{t_s+\Delta t}, r_{t_s+2\cdot\Delta t}, \dots, r_{t_f}\}$ is an array of power consumption rate at each time interval between t_s and t_f. Δt is time interval at which data collector service and scheduling service is working.
- Energy Consumption for vehicle n: E_n, denotes the energy consumed within each charging session. E_n can be computed as:

$$E_n = e_{tf} - e_{ts}$$

where e_{tf} and e_{ts} are accumulated energy consumption value read from meter at session start time and finish time, respectively.

Note that $t_f \leq t_l$ holds by the definition, which is obvious when vehicle is fully charged before departure. If vehicle leaves unexpectedly before battery is full, the charging session will be terminated by scheduling algorithm automatically and $t_f = t_l$ in this case. Another important parameter, stay duration d_n can be obtained by $t_l - t_s$. In later section, r_t will be the decision variable in our problem formulation.

➢ Inference for EV Charging Parameters

Decisions made by scheduling algorithms are based on the real-time data collected from EVSEs in time series. Unfortunately, there does not exist explicit signals from EVSEs, indicating termination of a charging session. Thus, proper inference is needed to determine some of the aforementioned parameters, such as leave time.

- Determine when to close a charging session

Scheduling algorithm must adaptively check if power consumption rate falls below a threshold. However, at the end of charging sessions, power drawn by some types of EVs is not stable, which might be caused

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by different designs of internal Battery Management System (BMS). Therefore, we employ a method based on moving average to adaptively evaluate the power consumption rate.

Assume the real-time power data for each meter at time t is denoted by y_t. The action to close a charging session is determined by a parameter for the averaged power consumption level, denoted by c_t, which can be calculated by:

$$c_t = \frac{1}{H} \cdot \sum_{i=1}^{i=H} y_{t-i-1}$$

where H is the length of moving window, 10 in our case. When the average power consumption level c_t drops below a pre-defined threshold $\underline{c}$, 0.1 kW in our case, the close charging decision will be made. Figure 67 illustrates this inference process:

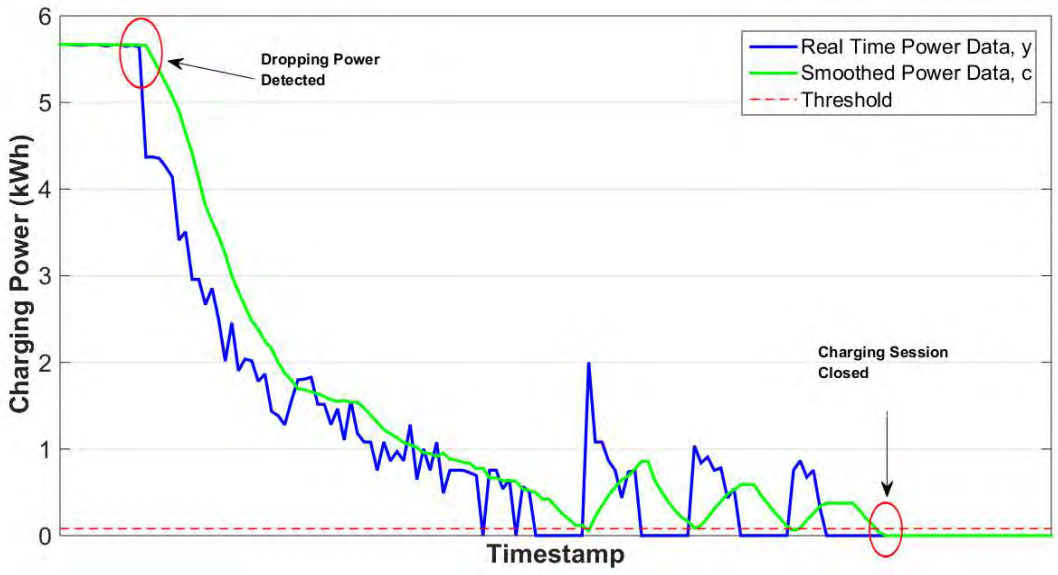


Figure 67 Inference Process to Close Charging Sessions

In addition, by evaluating the latest power data before closing the charging session, one can infer whether or not EV is fully charged. If the power value is still higher than the threshold, the plug is believed to be disconnected by the user when the charging is still in process.

- Determine leaving time

Leave time can also be inferred from time series data by detecting the earliest time when plug-in status changes to negative. The inference is illustrated below:

$$t_l = \begin{cases} t_f, & c_{tf} > \underline{c} \\ min(t), & c_{tf} \leq \underline{c}, t > t_f \; where \; pl(t) = 0 \end{cases}$$

If the power consumption rate when charging session is being close, c_{tf} is larger than the threshold, $\underline{c}$, the time to close charging session is exactly the leave time because the vehicle is believed to be manually

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un-plugged. On the other hand, when power consumption is lower than threshold, the leave time can only be inferred from the time when plug-in status changes from 1 to 0. $pl(t)$ denotes the plug-in status at time t.

- Parameter Estimation based on Historical Records

Based on the existing dataset, the objective is to extract features of EV energy consumption patterns and then apply it into scheduling algorithms. According to the observations, we find the charging behaviors, especially the parameters aforementioned have strong user dependence. A typical user's schedules are illustrated in Figure 68.

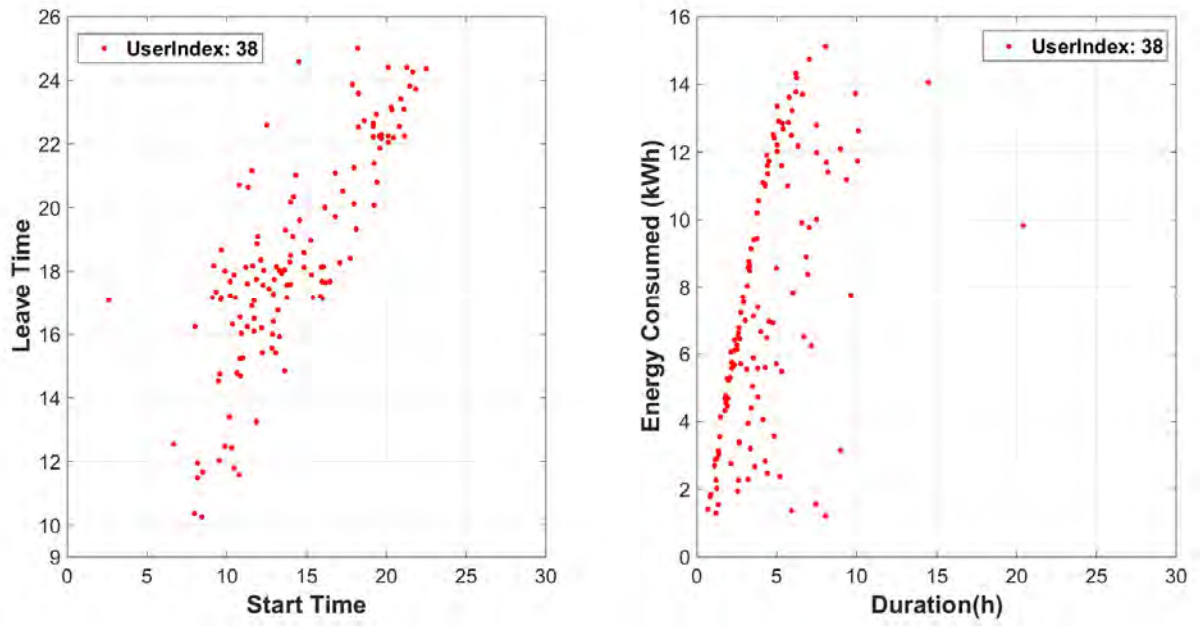


Figure 68 Charging Patterns for a Typical User

According to the visualizations above, leave time generally follows a linear relation with start time for this specific user. Similarly, the longer this user stays, the larger portion of energy can be consumed. This behavioral pattern represents a category of users, whose charging session parameters can be estimated using similar methods. We only display one typical user category, because the following estimation algorithm can also be applied to other categories.

At each time interval, after scheduling algorithm initiates, the estimation of stay duration and expected energy consumption are needed. A simple estimation method is utilized, which searches similar historical charging sessions for specific user index and calculate the average energy consumption and stay duration. For the purpose to extract features for historical charging sessions, the data structure we use to describe one charging session is a 5-tuple, which is defined as:

$$s \coloneqq (u, t_s, t_f, t_l, e)$$

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where u is the user index to which this session belongs; e is the energy consumption calculated by (1).

The expected energy consumption and expected stay duration can be estimated by

$$\hat{e} = \frac{1}{M} \cdot \sum_{i \in M} S[i].e$$

$$\hat{d} = \frac{1}{M} \cdot \sum_{i \in M} S[i].t_l - S[i].t_s$$

where$S[i].t_s \in [t_{s0} - \Delta t, t_{s0} + \Delta t]$, $(S[i].t_l - S[i].t_s) > t - t_{s0}$ and M denotes the count (length) of qualified sessions.

The time t when scheduling algorithm initiates the estimation request and the start time for current charging session t_{s0} are sent to estimation function as inputs. The estimated stay duration $\hat{d}$ and energy consumption $\hat{e}$ are the results as output. The detailed method to implement this function is shown in Figure 69. First, the algorithm will search neighbor sessions in terms of start time and duration. Then average value for the neighbors will be used as estimation for current session. However, If it does not have such neighbors, it is believed that current session belongs to a relatively new user in the system. Thus, preset value Δe and Δt_d will be used as short term estimations so that scheduling algorithm can frequently check this charging session.

Algorithm: Estimate Energy Consumption and Stay Duration

Input: $t, t_{s0}, UserIndex$
Output: $\hat{e}$, $\hat{d}$
Extract historical sessions: S, where $S.t_s \in [t_{s0} - \Delta t, t_{s0} + \Delta t]$ and $(S.t_l - S.t_s) \geq t - t_{s0}$ and $S.u = UserIndex$
if $S.length \geq 0$
estimate energy consumption $\hat{e}$ and stay duration $\hat{d}$
else
$\hat{e} \leftarrow e + \Delta e$
$\hat{d} \leftarrow d + \Delta d$
end

Figure 69 Estimation Algorithm Energy Consumption and Stay Duration

ECSA is designed to dynamically compute EV schedules according to the random user behaviors. As an EV scheduling algorithm, it aims to achieve better energy delivery efficiency and minimize the operational cost for system administrator, meanwhile satisfying EV charging demand from users. Our implementation assigns each thread to each EVSE, hence our scheduling algorithm works at EVSE level without other interferences. In this case, we assume there exists a selfish operator, who wants to minimize operational cost in monetary terms by shifting charging load to time zones where energy price is lower and maximizing the usage of renewable energy. For simulation purpose, we assume there exist several PV panels connecting to our EVSE.

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3.5.7.3. Problem Formulation

- User Model

As discussed above, each charging session for user n can be described by the aforementioned parameters defined in the tuple $s_n \coloneqq (u_n, t_{n,s}, t_{n,f}, t_{n,l}, e_n)$. Thus, the ideal scenario is that scheduling algorithm allocates more energy than expected, i.e. $e_n > \widehat{e_n}$, before user n leaves. e_n increases as the charging process goes on.

$$e_n(t) = e_n(t - \Delta t) + r_n(t) \cdot \Delta t, \qquad \forall t \in \left[t_{n,s}, \hat{t}_{n,f}\right]$$

$$e_n\left(t_{n,f}\right) \geq \hat{e}_n$$

- EVSE Model

Since the EVSE in this algorithm can be equipped with multiple power sources and certain outlets may share the same power source, which adds one more constraint that total power drawn from each power source cannot exceed its upper limit. In addition, power consumption rate at each outlet cannot exceed the maximum value for that power source:

$$0 \leq r_n(t) \leq r_k^{max} \cdot \eta, \qquad \forall t \in [t_{n,s}, \hat{t}_{n,f}]$$

Where r_k^{max} denotes the limitation from for power source k. Let $k =: \{1,2, \dots, K\}$ denote the order of power source number in one EVSE. For each power source k in the EVSE, we have:

$$0 \leq \sum_{n \in N_k} r_n^k(t) \leq r_k^{max} \cdot \eta, \qquad \forall t \in [t_{n,s}, \hat{t}_{n,f}]$$

where N_k denotes the charging sessions for power source k.

- Energy Price and Solar Generation

Energy price represents cost for unit energy consumption at different time instant. Real-time pricing have been proposed and implemented in several regions within United States. In a broader sense, energy price can also be cost in other forms, such as reliability, battery degradation or other operational cost. The price list is virtually created to represent demand and supply for a single day.

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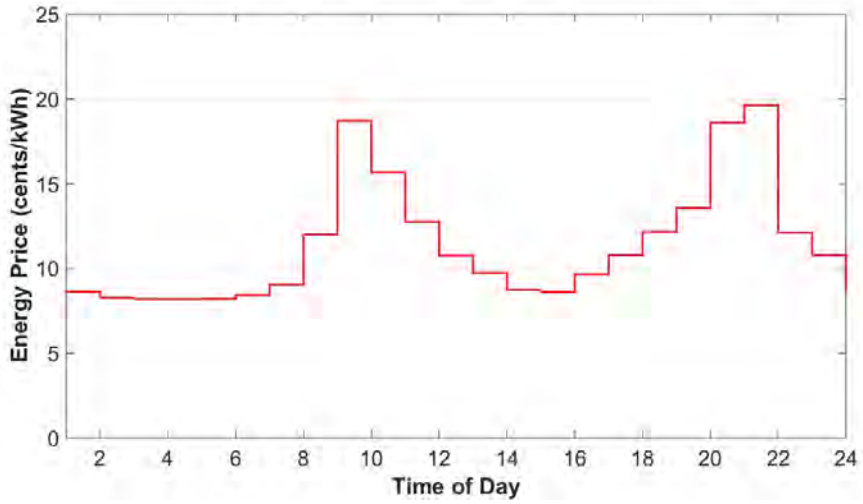


Figure 70 Sample Energy Price Used for Simulation

Numerous researches on solar energy prediction, both short-term and long-term have been conducted. The detailed approaches for solar generation prediction are out of scope of this algorithm. We simply apply day-ahead prediction and use that to make charging decisions. According to the observation from integration project at UCLA Ackerman Union. Each panel has an approximate 0.28 kW peak power output and we assume 10 panels are connected to support for one EVSE. The predicted PV power curve for a typical sunny day is displayed in Figure 71:

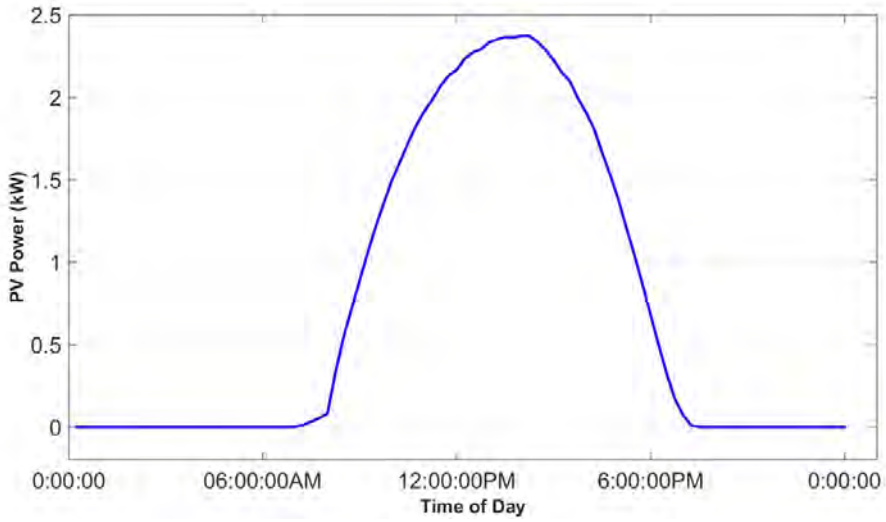


Figure 71 Sample Solar Power for a Sunny Day

Global objective function for all outlets in each EVSE is defined by:

$$min \sum_{t \in T} max\{\sum_{n \in N} r_n(t) - PV(t), 0\} \cdot P(t) \cdot \Delta t$$

s.t. constraints in EVSE model and user model.

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$PV(t)$ denotes solar output at time t, and $p(t)$ denotes the energy price at time t. When total power consumption is larger than the renewable generation, system operator has to buy additional power from electric grid to satisfy charging. Note that $\hat{e}_n$, $\hat{t}_{n,f}$ are both conditional estimations based on users' historical records, which are computed every time as the scheduling algorithm is triggered by pre-defined events. The schedules for next time interval will be updated based on computation results until new event is triggered.

3.5.7.4. Implementation of Event-based Scheduling Algorithms

- Event Definition

The implementation is based on events defined in advanced to describe a significant change of scheduling variables, which makes it necessary to re-initiate the schedule computation. The following types of events are tentatively designed for triggers.

Event 1: New vehicle arrives and submits charging request at current EVSE.

Event 2: Vehicle leaves from EVSEs or finishes charging

Event 3: Energy already consumed exceeds the estimated one, which is believed as an abnormal behavior and we infer that this user needs more energy than consumed.

Event 4: Leave time exceeds the estimated one, which might indicate this user has extended stay or is waiting to get more energy.

- Scheduling Algorithm

Algorithm: Event-based Cost Scheduling Algorithm (ECSA)

Event Trigger:
for each power source $k \in K$
    $N_k \leftarrow$extract charging sessions at power source k
    for each $n \in N_k$
        evaluate and estimate $\hat{e}_n$, $\hat{d}_n$
    end
    Compute the optimal schedules
    update schedules for each charging session
end

Figure 72 Pseudocode for ECSA

Once any of the above event is detected by monitoring program on cloud-side, which is illustrated in Figure 72, scheduling computation will be triggered on that EVSE. Hereby, each of the charging sessions will be re-evaluated with the methods in from **ECSA**, considering the current check time. The last step is to solve optimization problem according to the parameters of all charging sessions. The new schedules will be updated for the following time intervals.

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3.5.7.5. Experiment setup

To set up simulation experiment, we randomly select 10 continuous days and extract the real charging sessions submitted on one particular EVSE in UCLA campus. The extracted charging sessions are ordered by the start time and labeled with power source number so that real charging events can be reproduced exactly. We use dataset for the past year as the base dataset, from which we can extract user historical behaviors and estimate energy consumption and stay duration. Δt, i.e. time interval for scheduling algorithm is set to *15* min.

3.5.7.6. Cost Saving and Load Shifting

As the primary objective, cost saved will be an important criteria comparing to original **ESSA**. Time-variant price curve and predicted solar generation are set as inputs for scheduling algorithm. Figure 73 shows scheduling results for 2015 Mar. 17th. Blue curve indicates the new load curve from **ECSA**.

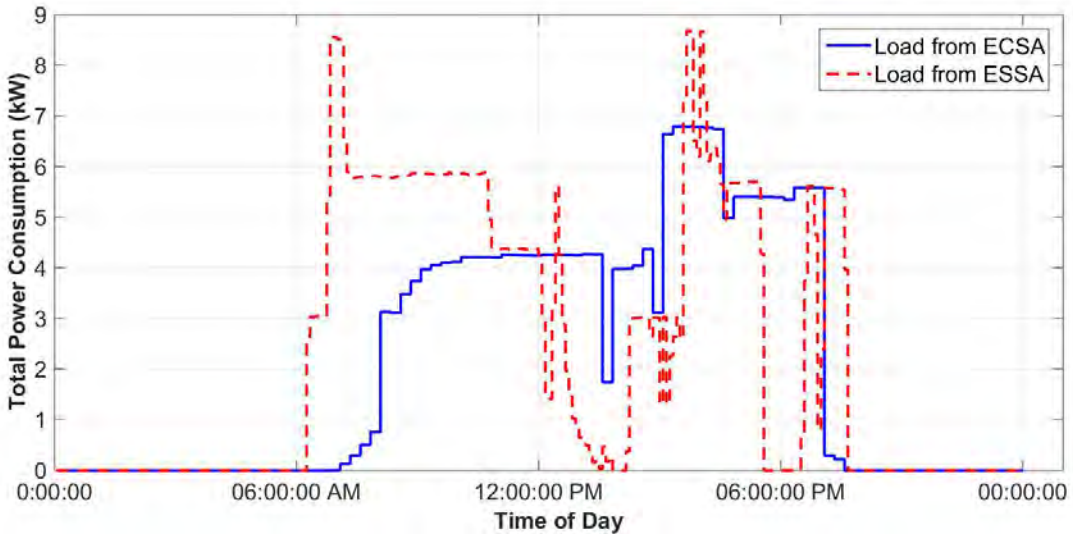


Figure 73 EV Power Consumption from ESSA and ECSA

It can be easily identified that **ECSA** can shift load to region with abundant solar energy and lower energy prices so that overall energy cost will be reduced. However, careful readers may notice that the area below blue line in Figure 73 is slightly smaller than that of red, i.e. less total energy from **ECSA** is consumed compared to **ESSA**. That is because exceptions, i.e. estimation errors, exist during the scheduling process. As the first vehicle arrives, the scheduling algorithm cannot predict behaviors information for other users, who might come later to share the same power source with current user. Thus, **ECSA** naively schedules higher power consumption to preferable time range. With the realization of new charging sessions with the same power source, **ECSA** starts to consider power source limitation and update charging schedules for previous user as soon as possible.

Figure 74 is the comparison of operational costs from 3 scheduling algorithms, **ESSA**, **ESSA** with solar integration and **ECSA**. Solar integration reduces the cost for both **ESSA** and **ECSA**. For **ECSA**, the cost decreases because of two reasons: 1) delayed energy consumption at the early stage of charging session 2) charging load shifted from regions with higher price and abundant solar energy, to regions with higher

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energy price and less solar energy. Suppose the energy consumptions are the same from **ESSA** and **ECSA**, there will still be larger portion of load in regions with lower price and ample solar energy, which can be observed from Figure 73. Thus, 1) is not dominant reason for cost reduction. The effectiveness of **ECSA** for cost minimization is demonstrated.

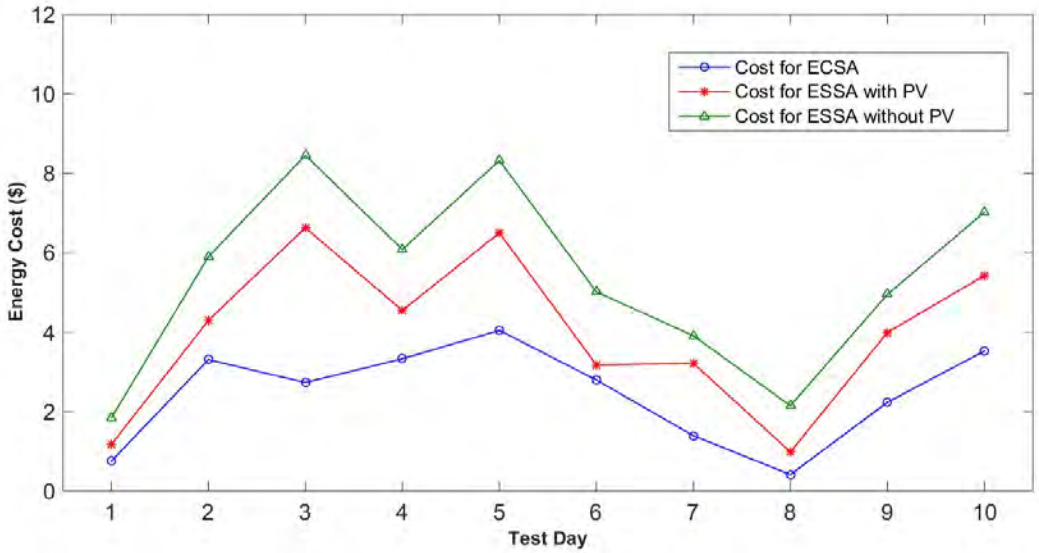


Figure 74 Operational Cost from EV Scheduling Algorithms

The other criteria is the deviation between actual energy consumption for each vehicle and that obtained from **ECSA**. A metric named Average Schedule Error Rate (**ASER**) is defined to represent this deviation:

$$ASER = \frac{1}{L} \cdot \sum_{i}^{L} \frac{e_i - e_{i,c}}{e_i} \cdot 100\%$$

where e_i is the actual energy consumption from **ESSA** for one charging session on a particular day. $e_{i,c}$ is the energy consumption from **ECSA**. L denotes the number of charging sessions on a particular test day. Smaller **ASER** value corresponds to less deviations. ASER values for the test days are generally acceptable considering the randomness of EV charging sessions. The energy consumption from **ECSA**, **ESSA** and **ASER** values are shown in Figure 75.

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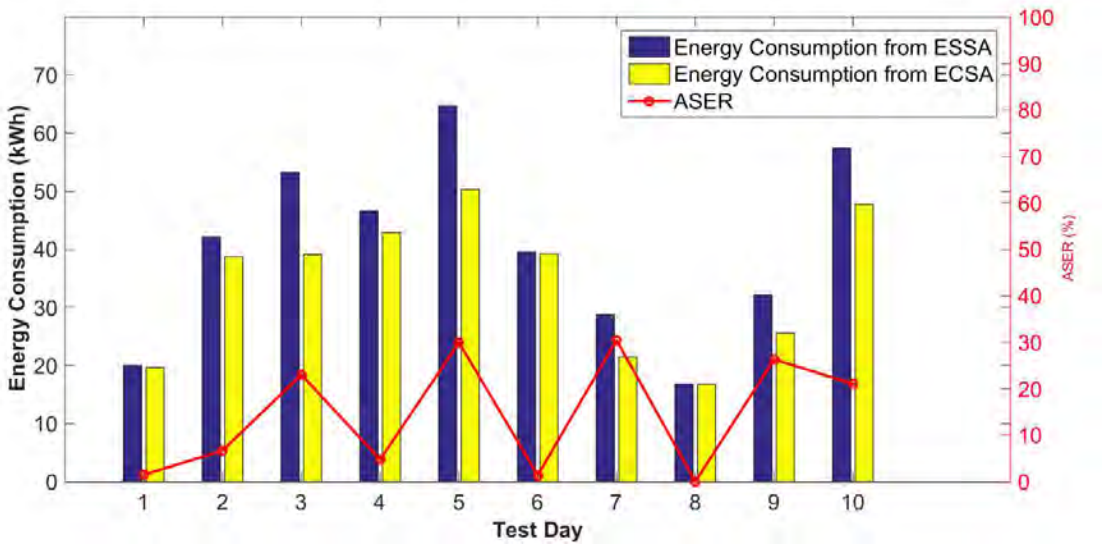


Figure 75 Energy Consumption and Error Rate

To achieve smaller **ASER** values, scheduling algorithm needs to deliver as much energy as the **ESSA** does before each session ends. There exist trade-offs between cost minimization and error rate minimization. Being greedy for energy cannot guarantee optimal cost and vice versa. A possible modification to current **ECSA** is to increase the greediness for charging sessions that start not long ago and then perform optimal scheduling after energy consumption reaches certain level. Hereby, cost saving performance can be preserved while global *ASER* values can also be improved.

3.5.8. Model Predictive Scheduling Algorithm to minimize load variance, considering uncertainty of user behaviors

In this section, we proposed a new real-time EV charging scheduling algorithm inspired by Model Predictive Control (MPC), which is designed and simulated in a micro-grid scenario, including building load, solar generation and EV load. A dynamic load estimation and a predictive optimization module are implemented to handle the uncertainties in system. The contributions of this algorithm can be summarized as: 1) Current-multiplexing is considered in the problem formulation and accordingly a virtual load for each EVSE is modeled to simulate the uncertain short-term EV energy demand. 2) Dynamic estimation method based on K-nearest neighbor (KNN) are utilized for charging session parameters. 3) Online predictive optimization method based on MPC is formulated, considering the uncertainties of building load and user behaviors; 4) IEC 61850 is utilized to standardize the information exchange by modeling the data involved in this algorithm, which gives practical meaning to more reliable and large-scale implementation.

The proposed system architecture is similar to that of even-based scheduling system. In general, the system has 5 main components, i.e. EVSE, building load, solar generation, client mobile application and a control center. Real-time energy consumption data with user index and device ID are retrieved and transmitted through advanced communication networks constructed within UCLA campus, and finally stored in a central database. EVSEs are controllable by commands from scheduling service on server side or client mobile applications, via assigning different duty-cycles to different outlets that share the same

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power source from the grid. The mobile application can perform the remote control function for each EVSE in our system. Based on the real-time power data from all engaged buildings, solar generation sites, EVSEs and mobile charging requests, scheduling services are able to compute periodically for an optimal EV energy scheduling given dynamic estimation of short-term energy demand. The building load used here is from Cornell University Facilities Service [17] and the solar data is from UCLA Ackerman Union Solar Integration project. To support reliable and large-scale implementation, IEC 61850 is implemented in EVSE gateways and the control center to encode/decode all the involved data and communication. This architecture has been tested by real EV users in UCLA and is friendly to more advanced charging algorithms.

3.5.8.1. IEC 61850 Protocol and Integration

EC 61850 is an international standard that provides a standardized framework that specifies the communication protocols, originally for power automation substation. The advantages include interoperability, free configuration and long-term stability. A specialized IEC 61850 gateway is designed as communication interface for both control center and EVSE in our system such that information exchange among system components, including EV charging stations and mobile applications, can be modeled within a unified framework, which increases the system interoperability. Data models, that include power information, EVSE status, charging requests and control signals, are all encoded as virtual components in xml-based messages to improve the system interoperability and reliability. Figure 76 is the schema view of communication and data modeling for EV system, based on IEC 61850 protocol.

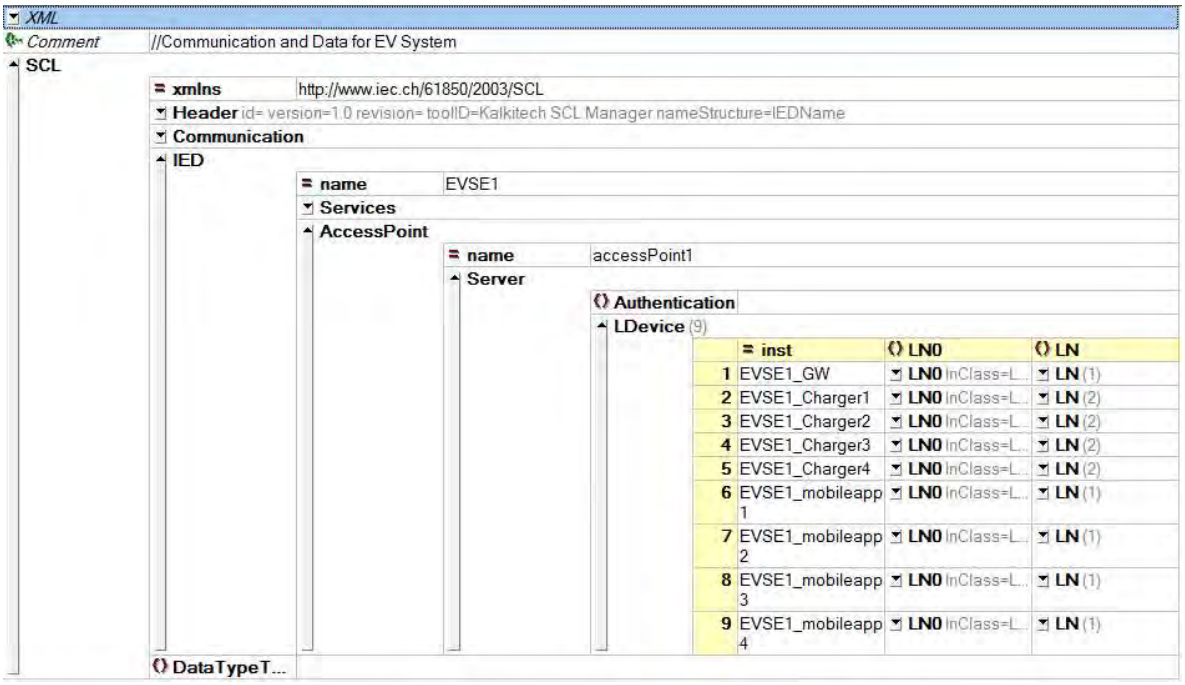


Figure 76 Communication & Data Modeling using IEC61850

3.5.8.2. Dynamic Parameter Estimation

The optimization method is inspired by Model Predictive Control (MPC), which is an online optimization method and computes optimal scheduling across fixed steps in the future periodically, however just

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realize the first element in the schedule results. The procedure continues in every step, taking the updated system states into consideration. In our system, the optimization program needs to involve the estimations of leave time and energy consumption values for all the active charging sessions. Thus, proper estimation methods play a significant role in improving the system performance. The leave time and energy consumption values are estimated dynamically, using the following methods.

3.5.8.3. Session Parameter Estimation

Each charging session, with a number of properties values, such as user index, device ID and start time, finish time, leave time and energy consumption, are stored as a record in database. We model each record associated with a charging session as a tuple:

$$s \coloneqq (u_n, t_s, t_f, t_l, e, d)$$

where u is the user index for this session, d is the EVSE ID or power source ID. t_s, t_f denotes the start time and finish time for the charging session, respectively; t_l is the leave time; e denotes the energy consumption. K-nearest neighbor (KNN) method is utilized to estimate e and t_f. In general, KNN calculates the weighted mean of neighbor values, who are among top k smallest distances with input value. In our case, the start time and stay duration in qualified sessions with top k smallest distances with current session value are extracted from database and averaged with weights.

$$dis_{i,j} = \left\| s_i.t_s - s_j.t_s \right\|$$

$$w_i = \frac{dis_{k+1,j} - dis_{n,j}}{dis_{k+1,j} - dis_{1,j}}$$

where $dis_{i,j}$ denotes the distance between session $s_i$and session s_j; $\mathrm{w_i}$ *denotes weight of the* ith *session* s_j.

$$\hat{e}_n = \frac{1}{k} \cdot \sum_{i=1}^{k} w_i \cdot (s_i.e)$$

$$\hat{t}_{n,f} = t_{n,s} + \frac{1}{k} \cdot \sum_{i=1}^{k} w_i \cdot (s_i.t_l - s_i.t_s)$$

where $\hat{e}_n$ and $\hat{t}_{n,f}$ are estimations of energy consumption and stay duration; k denotes the total number of qualified sessions.

3.5.8.4. Virtual Load Estimation

Since the hardware we are modeling in this algorithm has the power sharing and current multiplexing function, it means that the charging schedules for vehicles connected to the same power source will interact with each other. If taking uncertainties of future EV energy demands into consideration, the proposed system models an additional virtual EV load for each power source to account for the potential deviation. For each EVSE, historical data are extracted to construct the estimation of future EV load

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demand. Two steps are needed for dynamic virtual load estimation, i.e. total demand estimation and real-time update for remaining demand. Total demand after time t can be computed offline for all charging sessions in one specific EVSE:

$$D_t^k = \frac{1}{M} \cdot \sum_{i=1}^{i=M} s_i.e$$

where the qualified session s_i is subject to:

$$s_i.t_s = t$$

$$s_i.d = k$$

Real-time EV energy demand will be updated based on current active charging sessions in power source k and their estimated energy consumptions. The update for virtual load is illustrated in the following equation:

$$t_{v,f}^k = \max(s_i.t_f)$$

$$e_v^k = \max(0, D_t^k - D_{t_f}^k - \sum_{i \in N} s_i.e)$$

The virtual load charging rate $r_v^k(t)$ for power source$k$ is modeled as a regular EV load and will be input into the overall optimization problem.

$$0 \le r_v^k(\tau) \le r_v^{max}.\eta, \qquad \forall \tau \in [t, t_{v,f}^k]$$

$$\sum_{\tau=t}^{t_{v,f}} r_v^k(\tau) = e_v^k$$

3.5.8.5. Load Modeling with Uncertainties

- Building Load and Solar Generation

The power consumption for the building and solar power generation cannot be exactly known in advance and there exists little variation between different days. In our model, wiener filter and historical data are combined as a simple load predictor.

$$P_b(t) = P_b^e(t) + \overline{P_b(t)}$$

$$\overline{P_b(t)} = \overline{P_d(t)} - \overline{P_s(t)}$$

where $\overline{P_b(t)}$ denotes the average value of base load at the time t, which is the difference between average building power consumption value $\overline{P_d(t)}$ and the average solar generation value $\overline{P_s(t)}$. $\overline{P_d(t)}$ and $\overline{P_s(t)}$ can be simply obtained by averaging historical data for time t. The assumption for wiener filter is that the

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estimation error can be accumulated by previous steps and thus, real-time error calculation is performed by:

$$P_{b,t}^{e} = \sum_{i=1}^{i=T} \xi(i) \cdot f(t-i), \quad \forall t \in [1,T]$$

where $P_{b,t}^{e}$ is the error between real base load and predicted average baseload at time t. ξ is an identically distributed random variable with *zero* mean and variance σ^2. f is the impulse response of a causal filter, with following form:

$$f(t) = \begin{cases} 0, & t < 0 \\ a^{-t}, & t \geq 0 \end{cases}$$

Thus, the prediction error for current time t is only the summation of the previous estimation errors with different weights. Note, $f(0) = 1$.

- EVSE Model

Due to the characteristics of our EVSE design, more than one vehicle can share the power source at the same time, which means each charging session has separate constraints. For each connected vehicle, we use $r_n = \{r_{t_s}, r_{t_s+\Delta t}, r_{t_s+2\cdot\Delta t}, \dots, r_{t_f}\}$ to denote the power consumption rates from session start time t_s to session finish time t_f. Δt is the time step we use in this algorithm. The constraint for each charging session:

$$0 \leq r_v^k(t) + r_n^k(t) \leq r_k^{max}.\eta, \qquad \forall t \in [t_{n,s}, \hat{t}_{n,f}]$$

where $r_n^k(t)$ is the power consumption rate for vehicle n, which is connected to power souce k, at time t. r_k^{max} is the maximum power supply for power source k; η is the safety coefficient for this power source. $\hat{t}_{n,f}$ denotes the estimated finish time for vehicle n.

For each power source (EVSE), the same limitation of total power consumption also applies:

$$0 \leq r_v^k(t) + \sum_{n \in N_k} r_n^k(t) \leq r_k^{max}.\eta, \forall t \in [t_{n,s}, \hat{t}_{n,f}]$$

where N_k denotes the number of active charging sessions for power source k.

- User Model

Each charging session in our system is labeled with a number of properties, such as user ID, session start time $t_{n,s}$, session finish time $t_{n,f}$, vehicle leave time $t_{n,l}$ and the session energy consumption e_n. At the beginning of each charging session, estimation algorithm will calculate the predicted energy consumption $\hat{e}_n$ and the real energy consumption should be larger than the predicted value, but less than battery capacity E_n:

$$\hat{e}_n \leq e_n(t_{n,f}) \leq E_n$$

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As the time goes on, energy consumption is accumulated at each time interval:

$$e_n(t) = e_n(t - \Delta t) + r_n(t) \cdot \Delta t, \quad \forall t \in [t_{n,s}, \hat{t}_{n,f}]$$

3.5.8.6. Receding Horizon Control

At each time interval, the scheduler on control center will call optimization program to compute for an optimal EV charging schedule, considering the estimated travel schedules and energy consumption values for all active charging sessions. To minimize the overall load fluctuations, the optimization problem is modeled as:

Obj:

$$\min \sum_{\tau=t}^{\tau=T} (P_b(\tau) + \sum_{n \in N} r_n(\tau) - \frac{1}{T - t + 1} \cdot (P_b(\tau) + \sum_{n \in N} r_n(\tau)))^2$$

$s.t.$ constraints in user and EVSE model.

After the algorithm initiation, the base load that consists of building load and solar generation, and EV demand will be estimated. At each time interval, parameters for all active charging sessions in system will be extracted from database, and virtual load will be estimated to solve the optimization program. Only the first element in scheduling results $r_n(t)$ is used to control specific EVSE and then algorithm moves forward to next time interval. This procedure repeats until the end of the day. The whole algorithm is summarized in the following algorithm:

Algorithm: Predictive EV Scheduling Algorithm (PESA)
Calculate baseload $\overline{P_{b,t}}$ by averaging historical data
Estimate EV demand for each EVSE: D_t^k
$t = 1$
Do
Estimate $P_b(t)$ with error
For each vehicle $n \in N$:
Estimate leave time $\hat{t}_{n,f}$ and energy consumption $\hat{e}_n$ for vehicle n
End
Estimate virtual load parameters
Solve the constrained optimization problem
For each vehicle $n \in N$
Implement $r_n(t)$
End
$t = t + 1$
While $t \leq T$

Figure 77 Predictive Scheduling Algorithm

3.5.8.7. Experiment setup

Real-world charging records from users in UCLA campus are utilized for our experiment setup. One day in March, 2015 is randomly selected as a test day. There are totally 21 charging sessions from multiple users on test day, associated with all Level II EVSEs. We set the time interval for all data preprocessing and PESA

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to 15 minutes, which is long enough considering our problem size and performance requirement. The standard variance σ of ξ is set to *2* according to our observation and α is set to *0.4* in the wiener filter. Safety coefficient η is set *0.9*.

3.5.8.8. Scheduling Results and Future Improvements

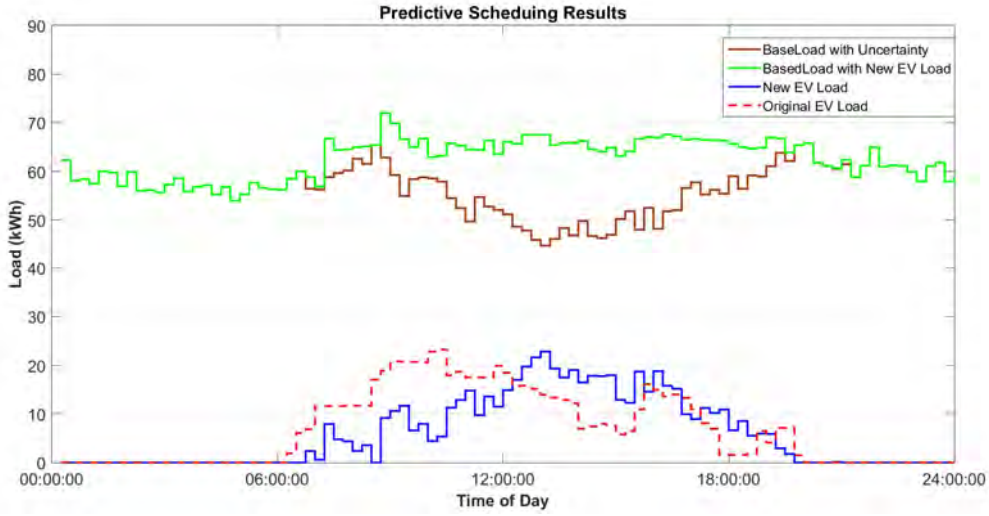


Figure 78 Predictive Scheduling Results

In Figure 78, the brown step curve is the baseload generated on the test day and the red dotted curve is the original EV load caused by the real-world charging behaviors. PESA is performed every 15 minutes and only the first schedule elements from the output is implemented. The blue curve is the new energy consumption schedules created by PESA. Visually, there is a portion of EV load is shifted from around 9:00 AM to 2:00 PM. Thus, the total load with EV, solar generation and building load is updated as the green curve in Figure 78. Thus, PESA's ability for valley filling is demonstrated.

Quantitatively, ASER value defined below can serve as a numerical metric load variation. After applying the updated EV load, the variation values for system loads with and without PESA are compared in Table I. Scheduled EV load with PESA can reduce the load variation drastically by more than 40%.

Table 6 Comparison of Load Variation

	With PESA	Without PESA
Load Variation	40.1413	70.7471

However, it should be noted that there is a slight difference between original total EV energy consumption and the new total EV consumption, which is reflected by the areas under the red-dotted curve and the blue curve, respectively. This deviation, caused by uncertainties of user behaviors, can be used as another criteria for performance evaluation. We define Average Schedule Error Rate (ASER) to represent this deviation:

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$$ASER = \frac{1}{L} \cdot \sum_{n}^{L} \frac{e_n - e_{n,c}}{e_n} \cdot 100\%$$

where $\boldsymbol{e_n}$ is the original energy consumption for one charging session. $\boldsymbol{e_{n,c}}$ is the energy consumption obtained from PESA. $\boldsymbol{L}$ denotes the number of charging sessions on a particular EVSE. Smaller ASER values denote less deviations and higher levels of satisfactions of energy demand from EV users. For each level II EVSE in experiment, single ASER is calculated as well as the overall value in Table 6.

Table 7 ASER Values for Different EVSEs

EVSE ID	EVSE 1	EVSE 2	EVSE 3	EVSE 4	Overall
ASER(%)	7.4061	24.6687	1.6531	19.6281	14.9745

After comparing different ASER values for different EVSEs, we find that, for EVSE 2 and EVSE 4, there are users, whose travel schedules and energy demands have quite large deviations from their historical routines, *i.e*, they leave unexpectedly at a much earlier time than before or demand much higher energy than usual. Even though the overall deviation level represented by ASER values are acceptable, users, whose daily charging behaviors are beyond estimations, will undermine the overall scheduling results. To solve this problem, the resemblance between current charging session and historical sessions should be estimated dynamically based on more information extracted from live system.

3.5.9. Analysis of Algorithms based on Data Collected

3.5.9.1. User Price Preference based on Experiment Data

Based on the experiment data collected from price based scheduling algorithms, tentative exploratory analysis can be conducted to identify user price preferences. As shown in Figure 79, a box-chart is provided to plot the history of price selections for users, whose overall number of charging sessions is ranked among the top twelve. One quick and simple observation is that behaviors for different users are quite diverse, with different mean values and variance. For instance, the user with id '160*' has a higher mean value than user 'EA0*' while his variance is smaller than that of 'EA0*'. In addition, the outliers for price selection data (lower value out of box) for different users are similar, which indicates most users very often tend to pick lower values than their average. One possible reason may be that users want to be 'safe' with their selections if it is not very urgent for them to charge at the EVSE. Thus, to take advantage of these observations, price strategies or charging scheduling algorithms for different users can be slightly different to achieve higher operational efficiency and profit.

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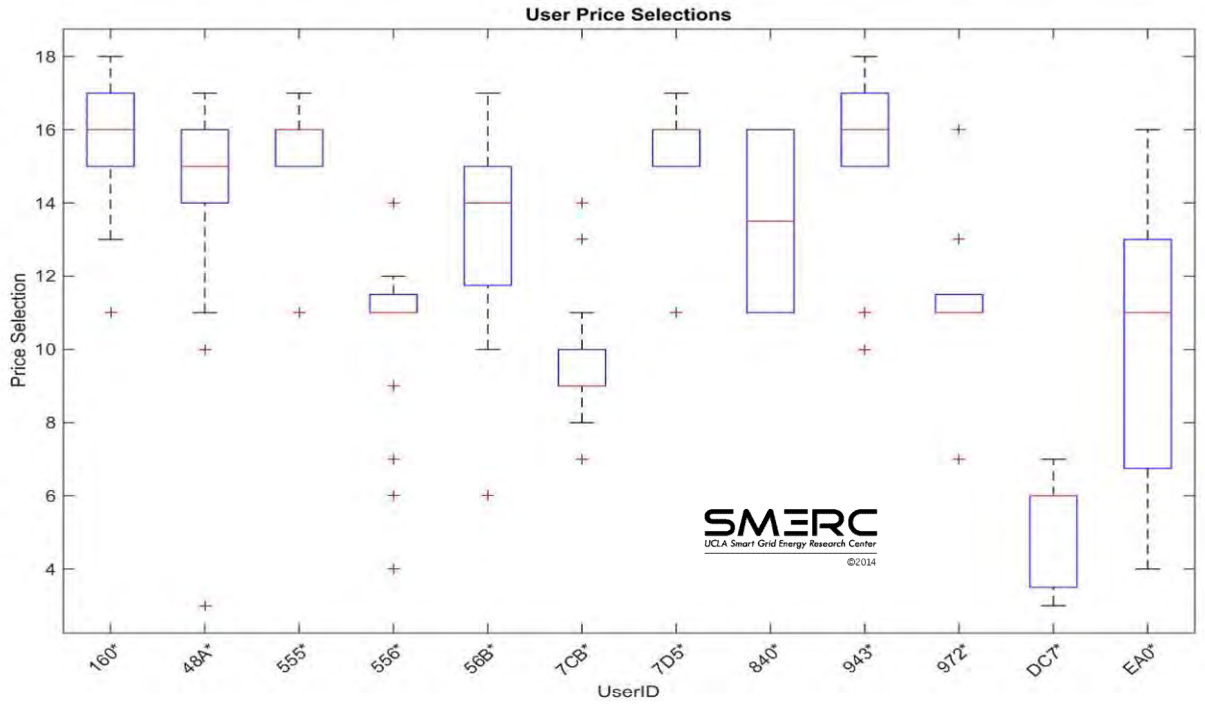


Figure 79. Box-Chart for User Price Selection

Similarly, for the same price selection data, bar chart comparison is also provided for further analysis. Two additional metrics are utilized here to evaluate the shape price selection history. Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean, which could be positive or negative. The positive value indicates the shape of distribution is right-skewed, while the negative value indicates a left-skewed one. Kurtosis is any measure of the "peakedness" of the probability distribution of a real-valued random variable. In a similar way to the concept of skewness, kurtosis is a descriptor of the shape of a probability distribution and, just as for skewness, there are different ways of quantifying it for a theoretical distribution and corresponding ways of estimating it from a sample from a population. All metrics are plotted in Figure 80. According to this figure, the 'skewness' and 'peakedness' are also quite varied.

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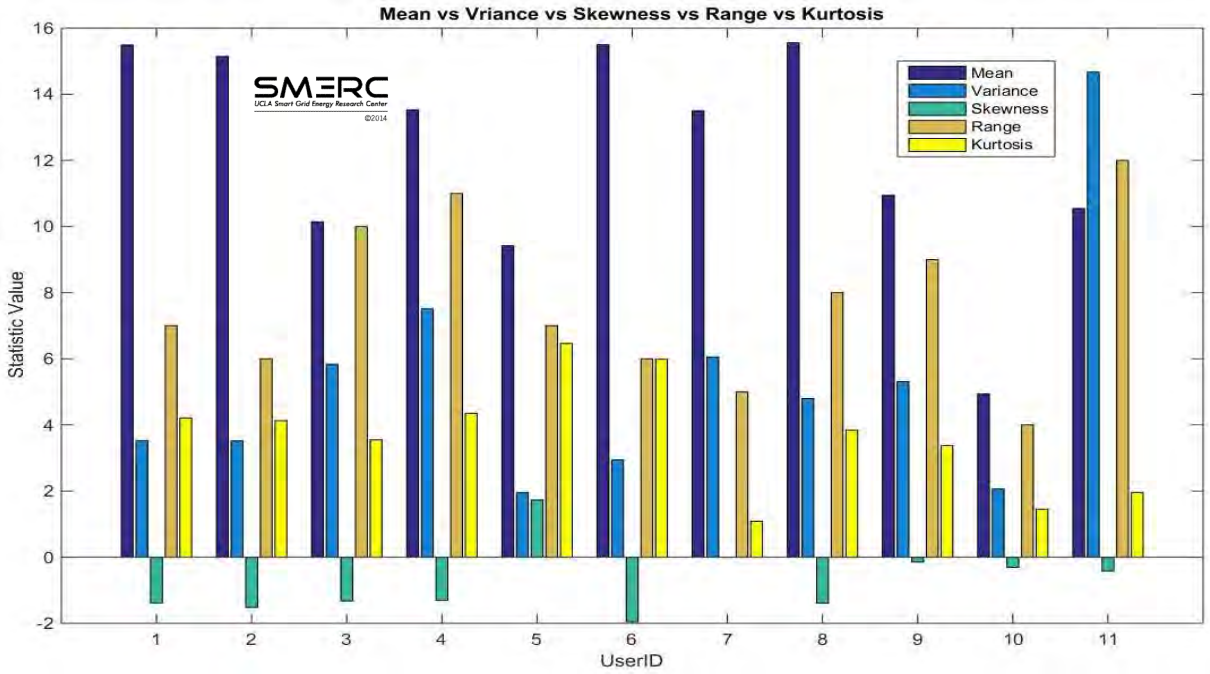


Figure 80. Statistics for Price Selections

Figure 81 shows overall relationship between stay duration and the energy consumption at Level I EVSE. The price selections are generally divided into 3 levels, i.e. high, low and medium labeled with different colors. Green spots represent high price selections; blue ones represent medium selections and the red ones represent the low value selections. The observation for the results is that there are relatively more red spots in the right-lower region, which means the energy consumption cannot be increased for the lower price selection. On the other hand, the green spots in the upper region indicate that a high price selection can usually result in higher energy consumption. This observation is reasonable because the sharing policy is actually determined by the selected price values for participating EV users. Thus, the advantage can be demonstrated by the result that the implemented algorithm offers more flexibility for users with different demands and requests, by selecting different price levels.

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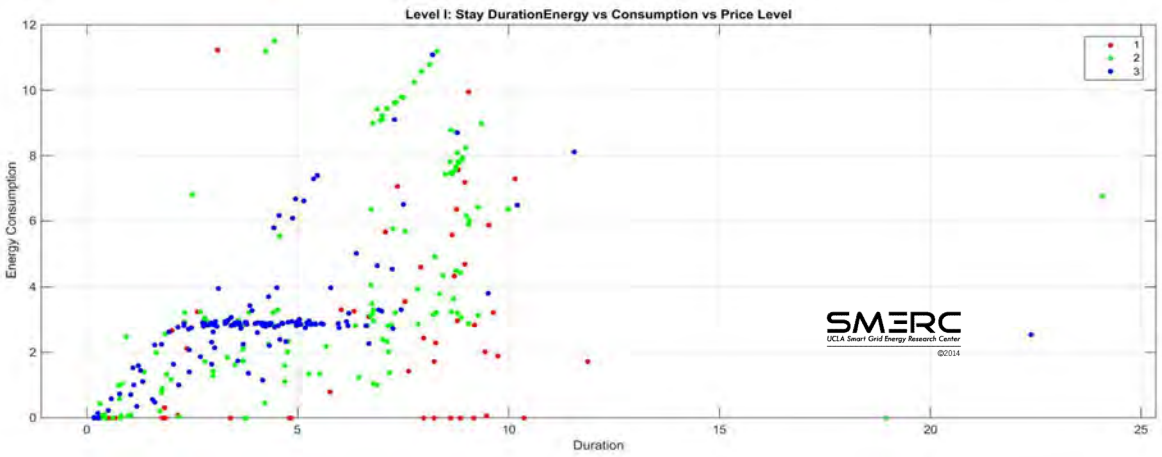


Figure 81. Impact of Price Selection on Charging Schedules

3.5.9.2. Considering Load Flattening and Random User Behaviors

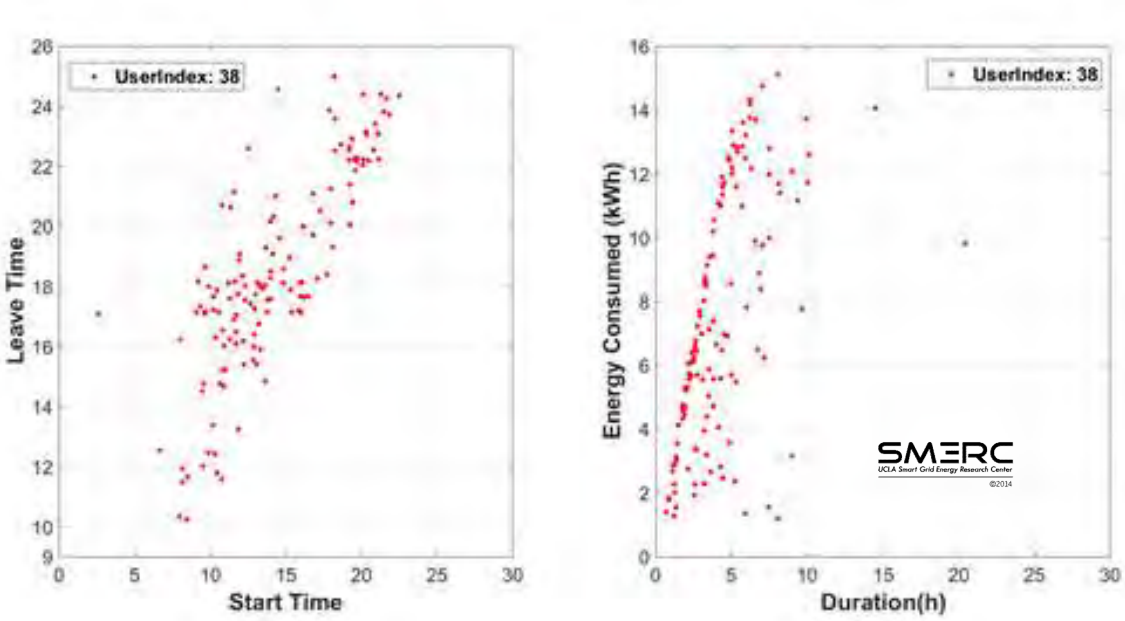


Figure 82. Charging Patterns for a Typical User

According to the visualizations above, the departure time generally follows a linear relation with the start time for this specific user. Similarly, the longer this user stays, the greater the amount of energy that can be consumed. This behavioral pattern represents a category of users, whose charging session parameters can be estimated using similar methods. We only display one typical user category, which can represent similar observations for other users. Another random factor for the scheduling algorithm is the predicted value of solar energy generation, which is illustrated in Figure 83 below.

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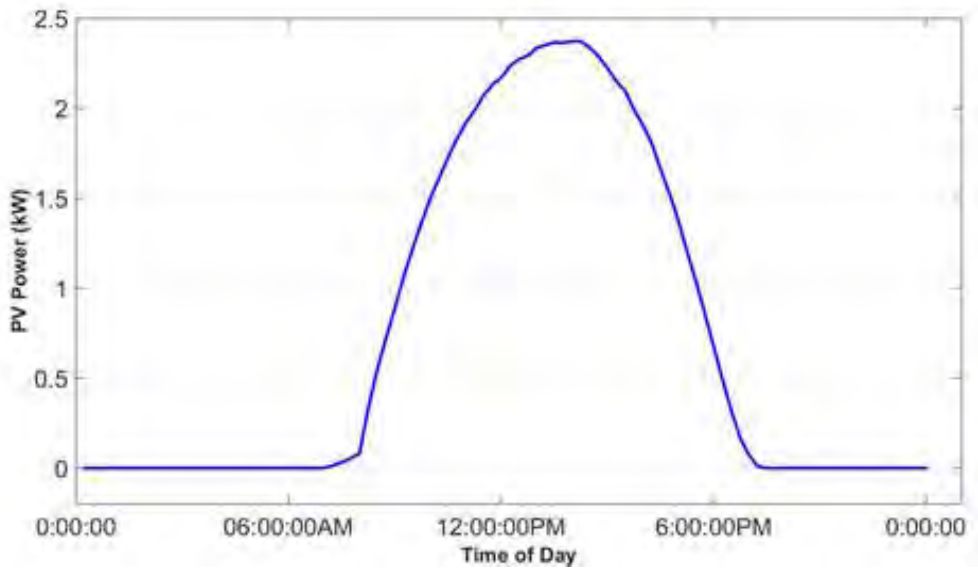


Figure 83. Sample Solar Power for a Sunny Day

Considering random EV user behaviors and solar generation for each EVSE, an event-based Scheduling Algorithm (ECSA) is proposed to manage multiple charging sessions based on the existing hardware design. As the primary objective, the cost saved will be an important criteria compared to the original Equal-Sharing Scheduling Algorithm (ESSA). Time-variant price curve and predicted solar generation are set as inputs for the scheduling algorithm. Figure 84 shows the scheduling results for 2015 March 17th. The blue curve indicates the new load curve from ECSA. It can be easily identified from the figure that ECSA can shift the load to a region with abundant solar energy and lower energy prices so that the overall energy cost will be reduced. However, careful readers may notice that the area below the blue line is slightly smaller than that of the red, i.e. less total energy from ECSA is consumed compared to ESSA. That is because exceptions, i.e. estimation errors, exist during the scheduling process. As the first vehicle arrives, the scheduling algorithm cannot predict behavioral information for other users, who might come later to share the same power source with the current user. Thus, ECSA naively schedules higher power consumption to the preferable time range. With the realization of new charging sessions with the same power source, ECSA starts to consider power source limitation and updates the charging schedules for previous users as soon as possible.

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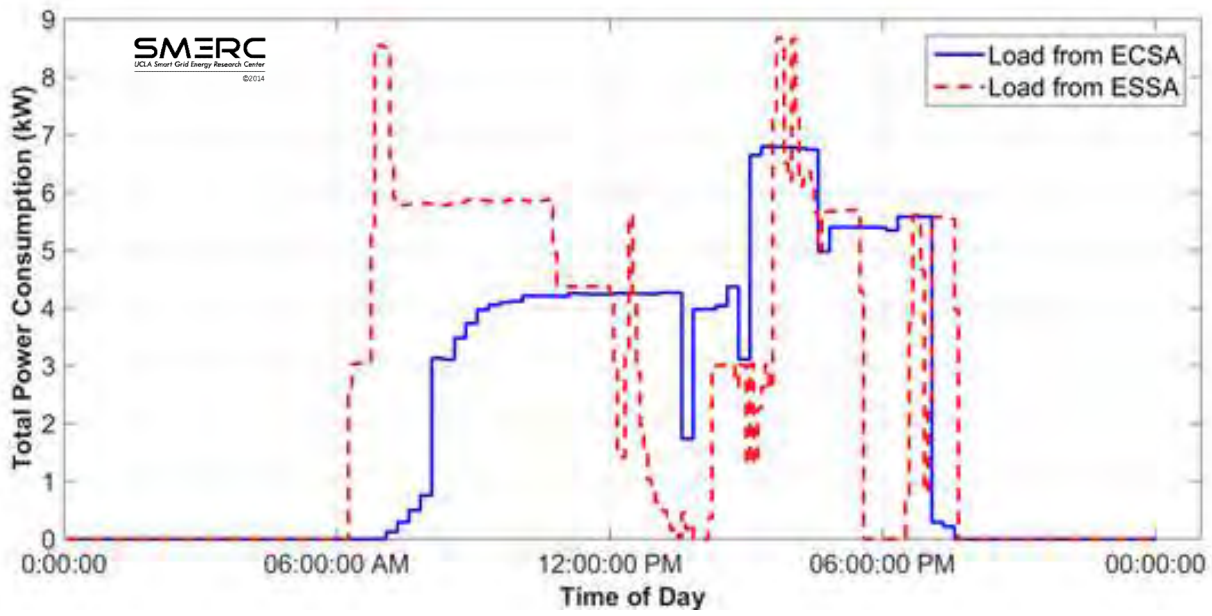


Figure 84. EV Power Consumption from ESSA and ECSA

Figure 85 is the comparison of operational costs from three scheduling algorithms: ESSA, ESSA with solar integration, and ECSA. Solar integration reduces the cost for both ESSA and ECSA. For ECSA, the cost decreases because of two reasons: 1) delayed energy consumption at the early stage of the charging session, and 2) the charging loads are shifted from regions with higher prices and abundant solar energy, to regions with higher energy prices and less solar energy. Suppose the energy consumptions are the same for ESSA and ECSA, there will still be a larger portion of load in regions with lower price and ample solar energy, which can be observed from the figure. Thus, the first reason is not enough for cost reduction. The effectiveness of ECSA for cost minimization is demonstrated

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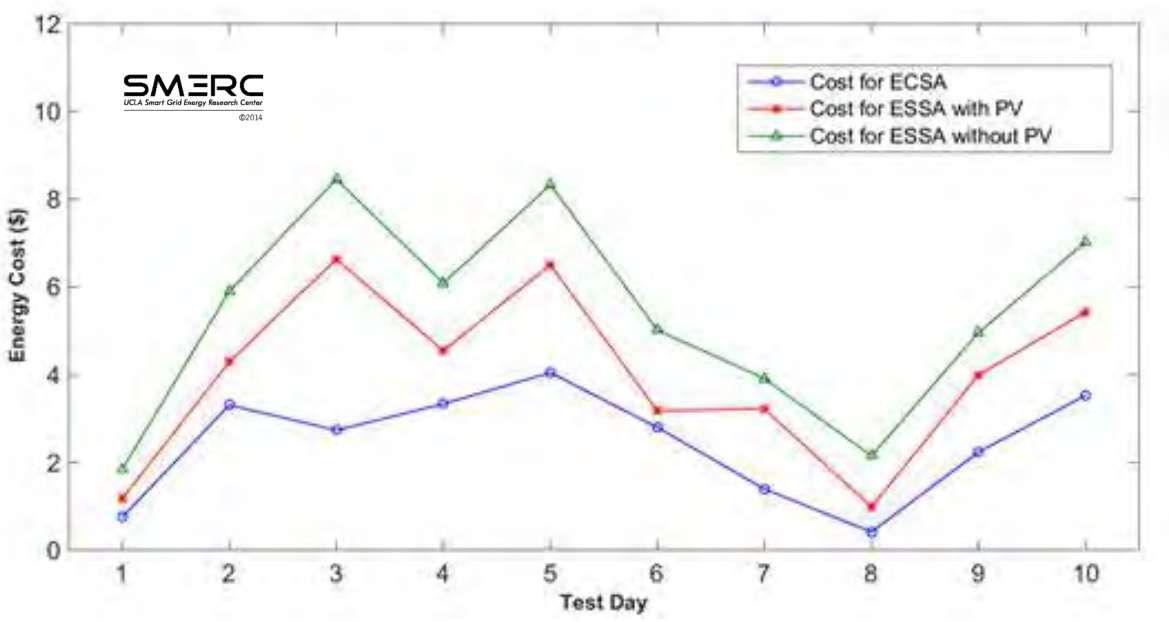


Figure 85. Operational Cost from EV Scheduling Algorithms

The other criteria are the deviation between actual energy consumption for each vehicle and that obtained from ECSA. A metric named Average Schedule Error Rate (ASER) is defined to represent this deviation:

$$ASER = \frac{1}{L} \cdot \sum_{i}^{L} \frac{e_i - e_{i,c}}{e_i} \cdot 100\%$$

where e_i is the actual energy consumption from ESSA for one charging session on a particular day. $e_{i,c}$ is the energy consumption from ECSA. L denotes the number of charging sessions on a particular test day. Smaller ASER values correspond to less deviations. ASER values for the test days are generally acceptable considering the randomness of EV charging sessions. The energy consumption from ECSA, ESSA and ASER values are shown in Figure 86.

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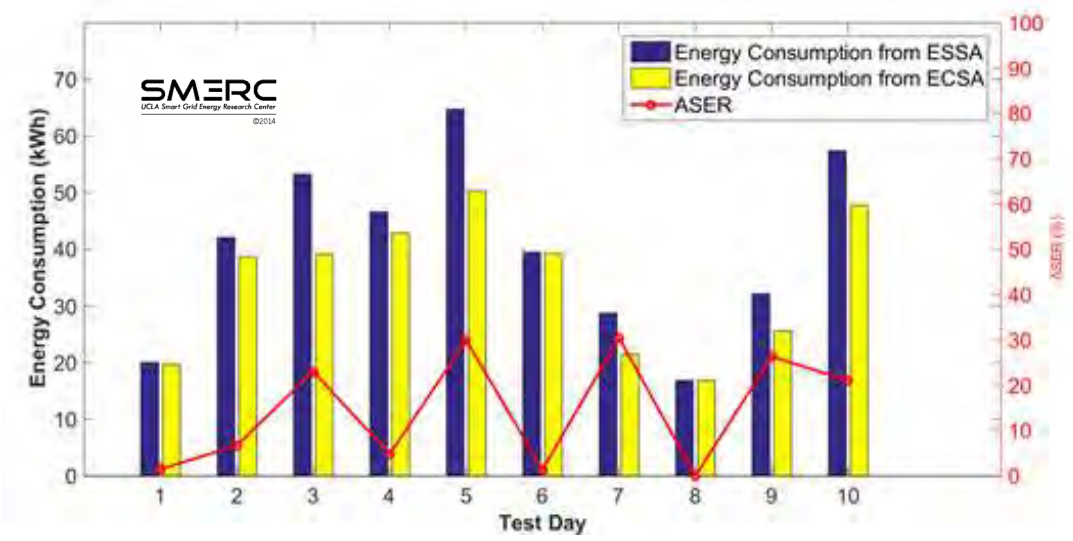


Figure 86. Energy Consumption and Error Rate

To achieve smaller ASER values, the scheduling algorithm needs to deliver as much energy as the ESSA does before each session ends. There exist trade-offs between cost minimization and error rate minimization. Being greedy for energy cannot guarantee optimal cost and vice versa. A possible modification to the current ECSA is to increase the greediness for charging sessions with recent start times and then perform optimal scheduling after energy consumption reaches a certain level. Thus, cost saving performance can be preserved while global *ASER* values can also be improved.

3.5.9.3. Fleet EV Analysis

Due to our observations on the UCLA campus, fleet EVs are more predictable than privately owned EVs because the work schedules for each vehicle are relatively fixed and stable. However, another observation is that most fleet EVs have multiple trips each day, which is different from privately owned EVs. In addition, multiple users may share the same vehicle. Thus, the modified way to represent the impact from fleet EV charging on the grid is to measure the energy demand probability distribution, which is generated by the statistics for each vehicle's charging history. For instance, a typical fleet vehicle's demand probability distribution is shown in Figure 87. The probability value goes up after 16:00 and drops after 24:00.

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Figure 87. Energy Demand Probability

Due to the fact that each vehicle has a probability distribution for its energy demand, proper clustering methods can be designed and implemented to group these vehicles into different categories based on their energy consumption patterns. This clustering will benefit the further advanced regulation programs for fleet EVs. A hierarchical clustering technique is employed to perform this clustering, whose results are shown in Figure 88 below. In this case, the number of groups is set to ten, which is determined by the overall number of users. Generally, different groups have obvious distance between each other, which can be identified by the height of each group in the dendrogram. More clustering techniques will be evaluated in the future.

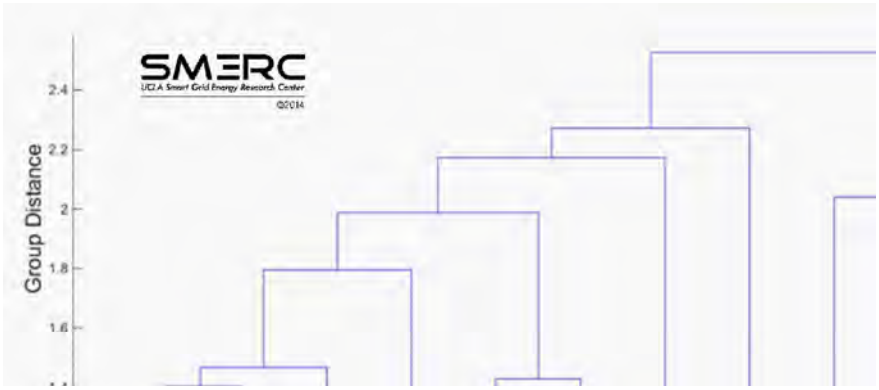


Figure 88. Fleet EV User Clustering

3.5.10. Future plan for Algorithm Development

3.5.10.1. User Charging Behavior Analysis

Historical data analysis is an important module in the proposed algorithm, which serves to estimate the number of charging and discharging operations in certain time ranges, based on the historical charging data. According to previous research, stochastic modeling of this data is significant in acquiring the

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distribution characteristics. WINSmartEV™ has accumulated more than 10 thousand charging records, which are helpful to implement simple forecast algorithms and exploit customer behavior models. We retrieve and plot the EV data from WINSmartEV™ database as shown in Figure 89:

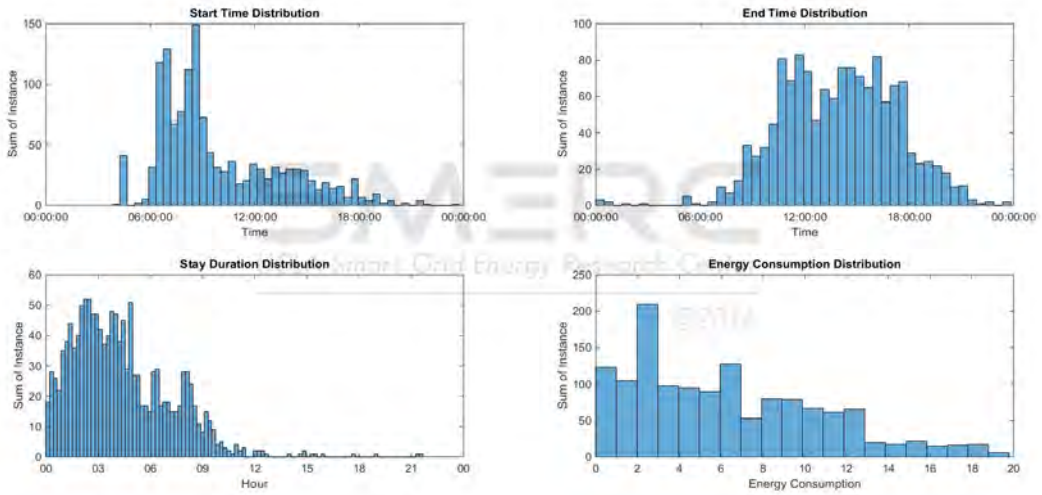


Figure 89. EV charging data for UCLA

For UCLA EV drivers, the distribution of arrival times is plotted in the upper-left subplot. The distribution is not strictly a Gaussian distribution and has two peaks, one in the very early morning and the other one around 10 AM. Intuitively, these behaviors are related to people's daily schedules on campus. Accordingly, the stopping time for charging has similar properties with two peaks, with less of a peak-valley difference. For fleet vehicles, which are owned and managed by the university, the attributes of their charging behaviors are much more obvious. First, the distribution for arrival and end times has only one peak with the center around 3:00 PM. Second, the distributions for the duration of stay and energy consumption are not Gaussian. Intuitively, these random arrival and departure behaviors can be modeled as Possion distributions; however, we must conduct more work and investigations to better characterize the data.

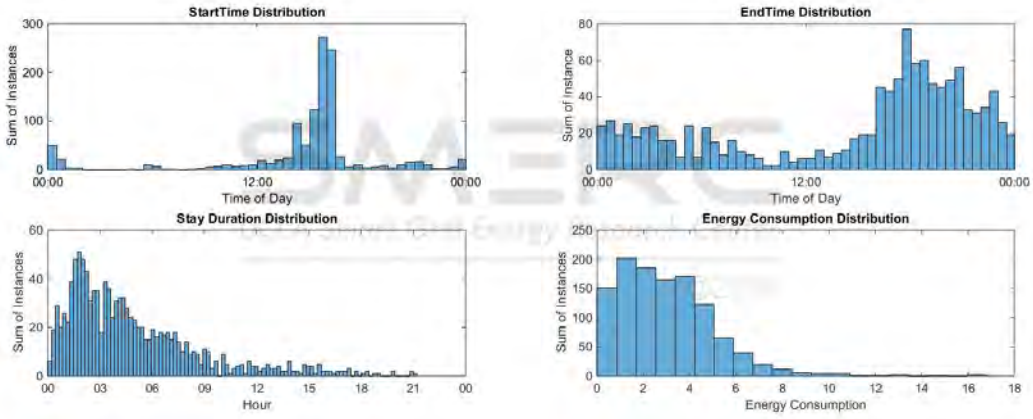


Figure 90. EV charging data for UCLA Fleet

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3.5.10.1. Nonparametric User Behavior Estimations

As shown in previous section, sparse user behaviors renders it difficult to accurately estimate session parameters for different users by using a universal model. Thus, according to the diverse properties of user behaviors, nonparametric method has the potential to adaptively calculate the probability for session parameters. Kernel method with a Gaussian distribution is a candidate for the solution since it can produce continuous distributions across the target dimension space and it asymptotically converges to the optimal estimations. Integration of kernel density estimation with our established EV energy management system is challenging due to 1) system architecture needs to be upgraded to support intensive kernel computations; 2) user behaviors should be preprocessed with proper algorithms before feature extraction; 3) evaluation and cross validation metrics should be studied to produce the most reasonable prediction.

3.5.10.2. Evaluation of Pricing Strategy and Demand Elasticity

Since we have been collecting data, more pricing and incentive strategies, i.e. TOU, CPP, RTP and PTR, can be implemented based the architecture with server-side smart algorithms and EVUser mobile App. Especially during peak hours, CPP and PTR can be combined to test customers' reactions to charging rewards or punishment. The ratio of lower price hours during the day will be altered to test low-price attraction to customers. Additionally, other popular reward programs can be offered via mobile App, such as coupon and discount for different classification of customers based on their historical charging behaviors. Thus, fairness for pricing schemes can also be tested with acquisition of charging load curves.

The customers' satisfaction rate can be reflected by their feedback through the Mobile App, which will help evaluate an important research topic: demand elasticity in a specific EV charging market, which is represented as an elasticity matrix E:

$$\begin{bmatrix} \frac{\partial q_1}{q_1} & \frac{\partial q_2}{q_2} & \cdots & \frac{\partial q_T}{q_T} \end{bmatrix}^T = E \begin{bmatrix} \frac{\partial p_1}{p_1} & \frac{\partial p_2}{p_2} & \cdots & \frac{\partial p_T}{p_T} \end{bmatrix}^T$$

where $E = \begin{bmatrix} \varepsilon_{11} & \varepsilon_{12} & \cdots & \varepsilon_{1T} \\ \varepsilon_{21} & \varepsilon_{22} & \cdots & \varepsilon_{2T} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{T1} & \varepsilon_{T2} & \cdots & \varepsilon_{TT} \end{bmatrix} \subset T \times T$, T is the total time intervals studied.

Similar to the starting time, different charging patterns for EV users can be analyzed. Estimating the potential movable energy from peak to valley will be an important task for the whole project. To accomplish the estimation, the energy consumption for every charging record, duration of every vehicle's parking, and users' price preference will be analyzed in the future, if available. In the end, all the related information is summarized to forecast the manageable energy for the current day.

Clustering means dividing the users into different groups according to their charging parameters and driving patterns. The dividing criterion can be based on a series of variables such as time of arrival, time of departure, arrival SOC, departure SOC, average energy consumed per charging, and miles every day, etc. To serve various purposes, different charging pricing strategies and policies can be designed to accomplish dissimilar functions. For instance, people who arrive early with a high SOC have a high potential to provide

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grid regulation support. In the end, the proposed algorithm satisfies the benefits of both the utility and users.

3.5.10.3. Charging Cost and Revenue Optimization

Based on the previous research of EV charging system modeling, a tentative version of the system modeling is created. This project can be classified as decentralized EV charging because the computation will handle every single user's charging requirement individually and asynchronously. That is to say, the control center will begin its optimization for a specific user when he or she presses the start charging button.

For every user, the objective is to maximize the profit by managing his or her vehicles' charging. As discharging is taken into account, the profit, including both charging and discharging scenarios, can be expressed as the following:

$$R = -\sum_{n_1=0}^{n_{cr}} \sum_{k=0}^{k_{cr}} (c(k) \cdot P_c(k) \cdot K_c + \alpha_c + \beta_c) + \sum_{n_1=0}^{n_{dr}} \sum_{k=0}^{k_{dr}} (c(k) \cdot P_d(k) \cdot K_d + \alpha_d + \beta_d)$$

$$+\gamma \cdot (S(k) - S_r)^2$$

Subject to the following constraints:

$$B(k+1) = B(k) + K \cdot c(k)$$

$$K = \begin{cases} K_c \cdot \eta_c \\ K_d \end{cases}$$

Ending criterion of this computation is:

$$S(k) = S_r$$

Where

R represents the revenue for a specific user.

n_{cr} is the number of ranges for charging the vehicle.

n_{dr} is the number of discharging ranges.

k_{dr} is the number of time slots in a specific charging range.

k_{cr} is the number of time slots in a specific charging range.

$c(k)$ is the charging step function.

$P_c(k)$ is the charging price in the corresponding time slot.

$P_d(k)$ is the discharging price offered by the utility.

K_c is the charging power for a specific vehicle.

K_d is the discharging power for the specific vehicle.

α_c is the battery degradation cost for battery charging.

α_d is the battery degradation cost for battery discharging.

β_c is the facility and service cost for battery charging.

β_d is the facility and service cost for battery discharging.

$B(k)$ is the amount of battery electricity in time interval k.

$S(k)$ is battery state of charging in time interval k.

η_c is the charging efficiency.

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s_r is the required state of charge by user when he or she leaves.

γ is the proportional factor which represents the system's desired orientation.

Right after submitting charging with a personal profile, including time of departure, accepted energy price and the expected SOC level, the system will confine the available slots for this specific user. Optimization will be within these time slots. Due to the complexity of users' schedules, there can be more than one charging and discharging range for a single vehicle. In this project, every 5 minutes in the horizontal time line is modeled as a slot, which is a unit for controlling charging behaviors. The revenue function includes the sum of the profits by offering regulation services, i.e. V2G discharging process, and the cost of getting power from the grid, i.e. charging. α, β indicates the facility service cost and battery degradation cost. As an optimization objective function, a driving term is added to the objective function, which serves to charge enough energy of the vehicle's battery as the user required at the beginning. If the battery state of charge reaches the required level by the user, optimization will terminate and $\alpha(k)$ over the time horizon will be the optimal charging schedule for this user. This tentative description is subject to be modified as more requirements of system constraints and objectives are needed.

3.5.10.4. Aggregated Charging and Discharging Control with DR Signal

By letting users participate in electricity market, utilities (aggregators) are able to apply dynamic pricing and promotion policies to regulate aggregated EV charging. Meanwhile, regulation signals can also be sent to EVs.

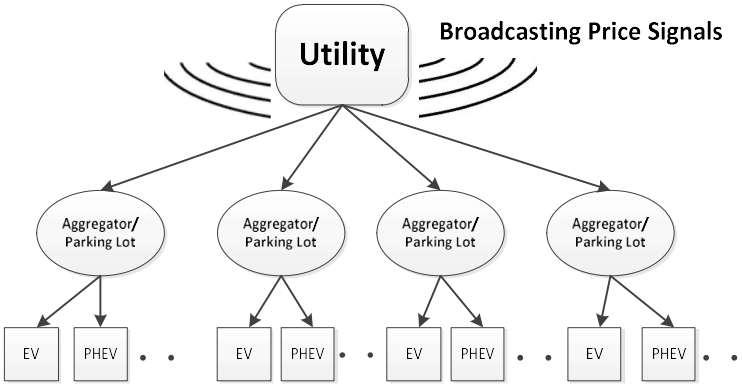


Figure 91. Emergency Load Curtailment Overview

Based on the historical data and load-forecasting model, the utility is able to know the available capacity for charging and discharging. If an unexpected and large load fluctuation is detected by the aggregator or utility, the utility should broadcast the updated price signal to its EV charging aggregators. The proposed algorithm on the user side is able to monitor the price change and trigger the optimization scheduling program on the server side again to update its schedule. Alternatively, the utility can directly control a fleet of EVs in response to the regulation signals. The anticipated scenario is that a number of EVs with enough energy in their batteries are ready to inject the energy back into the grid, before the electricity shortage or blackout occurs.

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3.6. Control Signal

As mentioned previously in section 3.1.3.2, according to charging interface standard SAE J1772 [18], the pilot signal of a Level 2 charging station uses the Pulse Width Modulation (PWM) format. Based on the pilot signal's duty cycle provided by the charging station, a PEV adjusts its load to meet the limitation; thus, using this characteristic of adjustment, a charging station is able to control the charging speed by changing the duty cycle of the pilot signal. We can use the control scheme between the pilot signals and PEV to create a current-sharing algorithm for the Level 2 charging station.

3.6.1. Hardware and Firmware design of the Various Current Multiplexing Charging System

Figure 92 shows the schematic of the peripheral circuit designed to generate pilot signals with variable duty cycles.

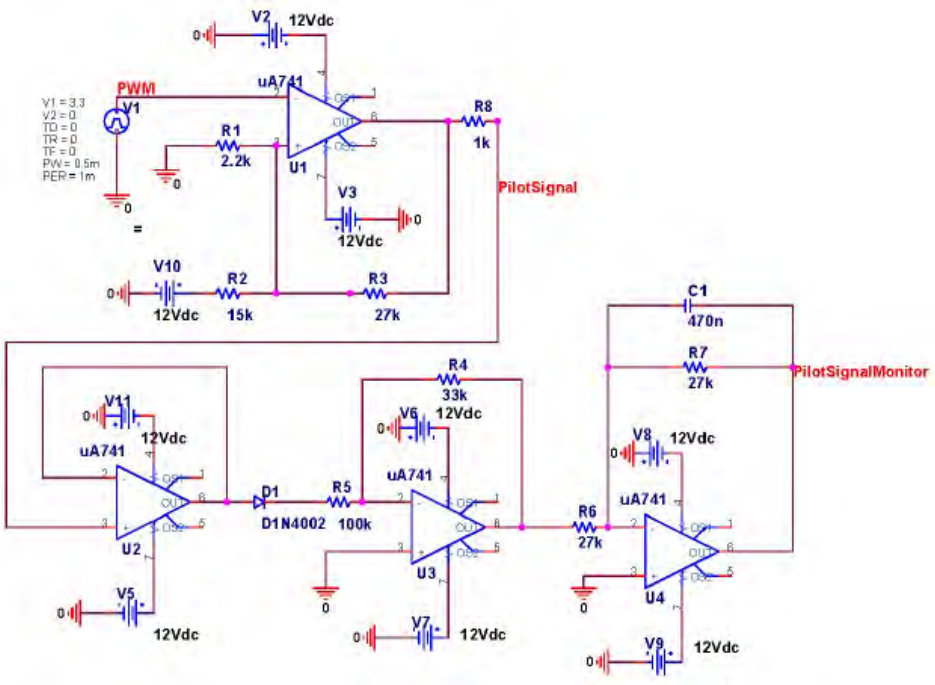


Figure 92. Peripheral Circuit of Pilot Signal Monitor [19]

As seen in Figure 92, the pilot signal generator produces a PWM signal that is amplified, when fed to the PEV, from 3.3V/GND to +/-12V by a Schmitt trigger. Following the Schmitt trigger is the unit gain which isolates the circuit in order to avoid a load effect on the monitoring circuit; note that a Schottky diode is inserted after the unit gain because only the positive part of the signal is monitored. For monitoring purposes, the pilot signal is de-amplified to fall within the A/D converter's range and fed through a low pass filter to produce a DC voltage. We do not use the peak value detection method because it tends to be affected by unexpected spikes producing unreliable measurements.

It has been observed that the A/D conversion of the pilot signal shrinks when the temperature inside the EVSE increases. The following measures are taken to mitigate this high temperature issue:

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1. Natural Ventilation: The controller chassis is punched with mesh so that the natural ventilation can effectively decrease the temperature inside the controller box.
2. Pilot Signal A/D conversion offset calibration and tracking: The A/D conversion offset of the Pilot Signal is calibrated during the charging initialization process. The offset value is dynamically adjusted when the temperature inside the controller box increases during the charging process.
3. Change Pilot Signal A/D conversion shrinking ratio: The A/D conversion shrinking ratio of the pilot signal can be slightly decreased in order to have a higher voltage at microprocessor end. Thus, the controller can have a higher resolution with four EVs plugging-in under a high temperature condition.

To ensure the power consumption of the EVSE is within the specified capacity rating, the total duty cycle of all four outlets is checked at the end of the charging initialization process. This issue was discovered when the next user would submit charging while the previous user's initialization process was not finished.

Four cases were tested in the experiments including: (1)0A to 12A, (2)12A to 0A, (3)8A to 12A, and (4) 12A to 8A, which covers the cases of switching between high and low current. The results are shown in Figure 93 to Figure 96. Channel 1 (yellow) is the current taken by the EV while channel 2 (blue) is the pilot signal.

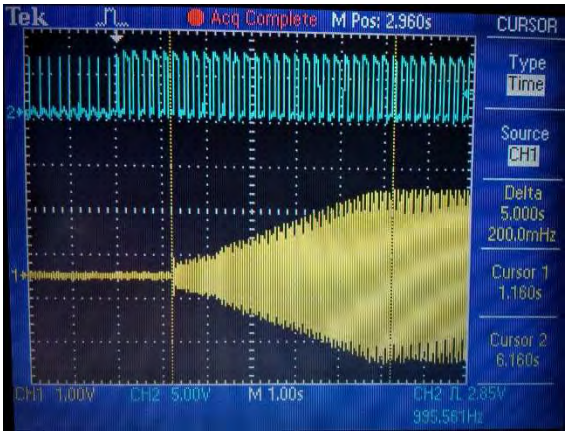
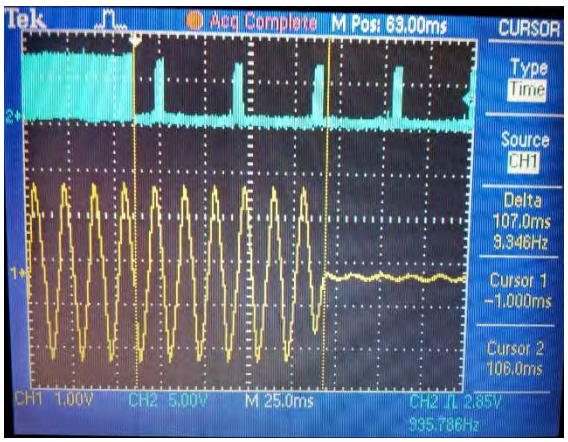


Figure 93. From 0A to 12A



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Figure 94. From 12A to 0A

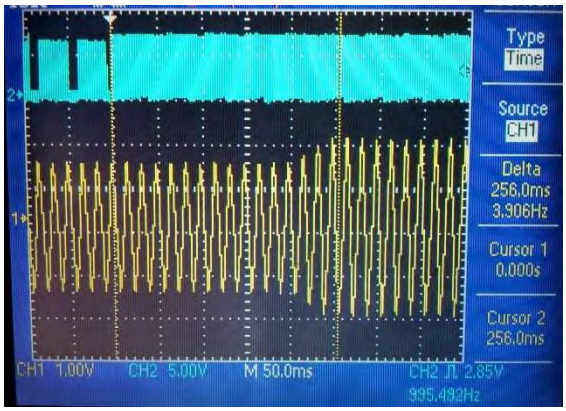


Figure 95. From 8A to 12A

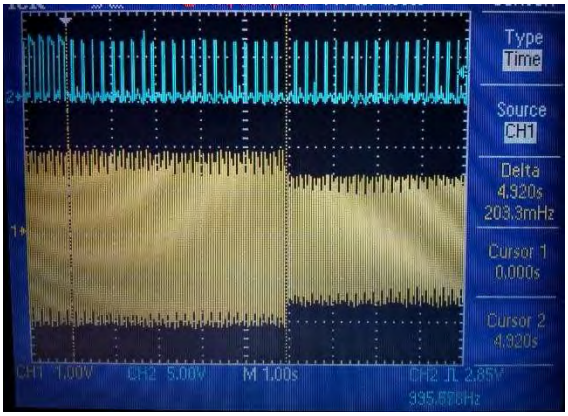


Figure 96. From 12A to 8A

Note that in the Level 1(110V) charging, even though the server sets the duty cycle larger than 20%, which makes the maximum current capable of being larger than 12A, the Nissan leaf will only take 12A. Here we define T_{EvExe} to be the time between the EV receiving the command and it starting to change the current, T_{EvResp} is the time between the EV starting to change the current and when it is settling down. T_{EV} is the summation of T_{EvExe} and T_{EvResp} which can be expressed in (1).

$$T_{EV} = T_{EvExe}(I_{init}, I_{final}) + T_{Ev\,\mathrm{Re}\,sp}(I_{init}, I_{final}) \qquad (1)$$

The experiments are summarized in Table 8. Notice that from the experiments, the T_{EvExe} and T_{EvResp} are related to both the initial current I_{init} and final current I_{final}.

Table 8 - EV response time with Nissan Leaf

	I_{init} (A)	I_{final} (A)		
		0	8	12

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T_{EvExe} (ms)	0		1000	1000
	8	100		250
	12	100	5000	
T_{EvResp}(ms)	0		3000	5000
	8	10		60
	12	10	60	
T_{EV} (ms)	0		4000	6000
= T_{EvExe}+ T_{EvResp}	8	110		310
	12	110	5060	

In the case of I_{final}=0A, T_{EvExe} is 100 ms and T_{EvResp} is 10 ms, which are relatively faster than other cases. It is possible that the EV could turn off its switch in 100 ms without changing its load and 10 ms is the transient response to 0A. In the case of I_{init}=0A, T_{EvExe} is 1000 ms and T_{EvResp} is proportional to the final current. It is possible that the EV turns on its switch in 1000 ms and starts to consume a current proportional to the final current. In the case of I_{init}=12A and I_{final}=8A, T_{EvExe} is 5000 ms. It is possible that the EV's battery management system needs to balance the battery cells and then change its load.

3.6.2. Design of RFID Mesh Network for Electric Vehicle Smart Charging Infrastructure

The experimental setup of the RFID response time test is shown in Figure 97.



Figure 97. Setup of RFID response time test

The response times for one-hop communication between a ZigBee coordinator and a ZigBee router are presented in Figure 98.

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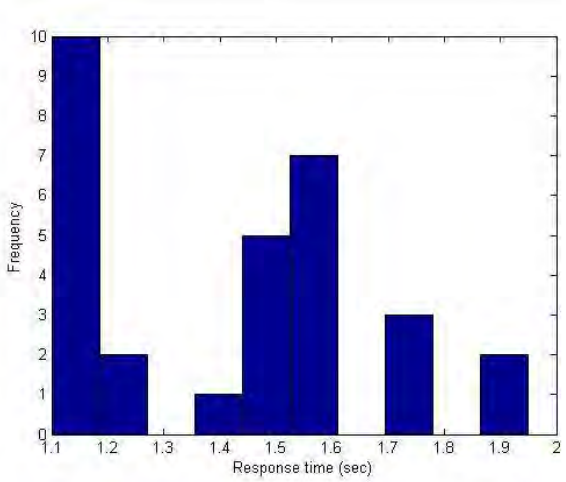


Figure 98. ZigBee router response times in 30 trial runs

The results show considerable variation in router response times, with an average delay being around 1.4 seconds. A two second minimum interval must be incorporated on the server to allow for message responses. An interval much larger than two seconds needs to be allowed for detecting an approaching EV. Figure 99 shows the results of RSSI vs. distance between charging station and EV.

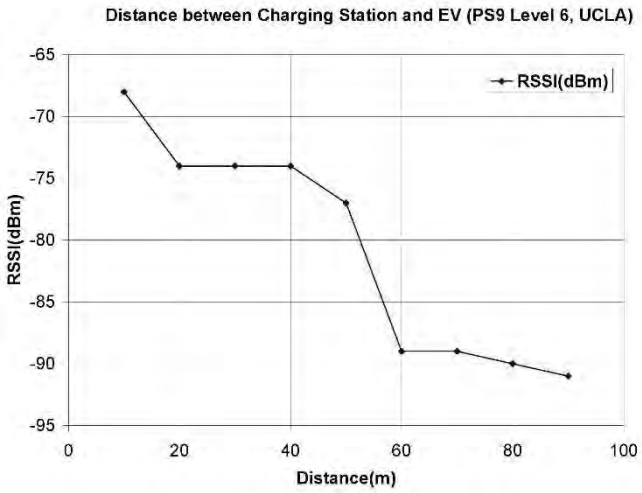


Figure 99. RSSI v.s. Distance between charging station and EV

The experiment shows that when the EV is within 50 meters of the charging station, the RSSI has a sudden jump -89 dBm to -77dBm. Although the theoretical range for ZigBee communication is 75 meters, the charging station would detect the EV at 50 meters in the real world. Notice that the RSSI has another jump when the EV approaches within 20 meters, which implies that RSSI would be an appropriate metric for identifying an EV approaching a charging station.

The accepted speed limit in parking garage is 5 mph, which means an EV approaches a charging station by 4.5 meters every 2 seconds. After an EV is detected at a distance of 50 meters and assuming that the EV

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parks 5 meters away from the charging station, the station has a maximum of 10 handshakes to determine whether the EV is approaching or leaving.

3.6.3. Analysis of results of operation/tests

The system performance while running a charging algorithm is analyzed in the following subsections.

3.6.3.1. Server Waiting Time for Duty Cycle Change

The experimental data can be represented by (1) and (2).

$$T_{EvExe}(I_{init}, I_{final}) = \begin{cases} 1000 & , I_{init} = 0 \\ 100 & , I_{final} = 0 \\ 250 & , I_{init} < I_{final} \\ 5000 & , I_{init} > I_{final} \end{cases} \quad (1)$$

$$T_{Ev\,\mathrm{Re}\,sp}(I_{init}, I_{final}) = \begin{cases} 400 \times I_{final} & , I_{init} = 0 \\ 10 & , I_{final} = 0 \\ 60 & , otherwise \end{cases} \quad (2)$$

Therefore,

$$\begin{aligned} T_{EV} &= T_{EvExe}(I_{init}, I_{final}) + T_{Ev\,\mathrm{Re}\,sp}(I_{init}, I_{final}) \\ &= \begin{cases} 1000 + 400 \times I_{final} & , I_{init} = 0 \\ 110 & , I_{final} = 0 \\ 310 & , I_{init} < I_{final} \\ 5060 & , I_{init} > I_{final} \end{cases} \end{aligned} \quad (3)$$

The time of returning the duty cycle T_{Return} is expressed in (4)

$$\begin{aligned} T_{\mathrm{Re}\,turn} &= T_{ControlUni\,t} + T_{GatewaySer\,ver} \\ &= T_{ZigBee} + T_{3gUplink} + T_{Cloud} \end{aligned} \quad (4)$$

Set $T_{waiting}$ to be the waiting time between the successful return from the change in the pilot signal duty cycle and the power information request, which is expressed in (5)

$$\begin{aligned} & T_{\mathrm{Re}turn} + T_{waiting} \\ & \approx \left(T_{ZigBee} + T_{3gUplink} + T_{Cloud}\right) + T_{waiting} \\ & \approx T_{3gUplink} + T_{Cloud} + T_{waiting} \\ & > T_{EV} = T_{EvExe}(I_{init}, I_{final}) + T_{Ev\,\mathrm{Re}\,sp}(I_{init}, I_{final}) \end{aligned} \quad (5)$$

Rewrite (13), $T_{waiting}$ is expressed in (6)

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$$
\begin{aligned}
&T_{waiting} > T_{EV} - T_{\mathrm{Re}turn} \\
&\approx T_{EvExe}(I_{init}, I_{final}) + T_{Ev\,\mathrm{Re}sp}(I_{init}, I_{final}) - \left(T_{3gUplink} + T_{Cloud}\right) \\
&= \begin{cases}
1000 + 400 \times I_{final} - \left(T_{3gUplink} + T_{Cloud}\right) & , I_{init} = 0 \\
110 - \left(T_{3gUplink} + T_{Cloud}\right) & , I_{final} = 0 \\
310 - \left(T_{3gUplink} + T_{Cloud}\right) & , I_{init} < I_{final} \\
5060 - \left(T_{3gUplink} + T_{Cloud}\right) & , I_{init} > I_{final}
\end{cases}
\end{aligned} \quad (6)
$$

From (14), $T_{waiting}$ depends on I_{init} and I_{final}. In [20], T_{Cloud} can be ignored compared with T_{3G}. Assume that $T_{3gUplink}$ is approximately half of T_{3G}, which is the round trip time between the cloud and the charging station. Therefore, (6) can be rewritten as (7)

$$
T_{Waiting} > \begin{cases}
1000 + 400 \times I_{final} - 0.5 \times T_{3G} & , I_{init} = 0 \\
110 - 0.5 \times T_{3G} & , I_{final} = 0 \\
310 - 0.5 \times T_{3G} & , I_{init} < I_{final} \\
5060 - 0.5 \times T_{3G} & , I_{init} > I_{final}
\end{cases} \quad (7)
$$

With further information from I_{init} and I_{final}, $T_{waiting}$ can be set to be variable values based on I_{init} and I_{final} rather than a fixed value in order to accelerate the performance of the system.

3.6.3.2. System Response Time

The time required for power information retrieval $T_{Retrieval}$ of four meters in a single charging station is expressed in (8)

$$
T_{\mathrm{Re}trieval} = 4T_{RoundTrip_3G} \approx 4\left(T_{3G} + T_{Metering}\right) \quad (8)
$$

With the Power Information Collector (PIC) proposed, only one time request is required and $T_{Metering}$ is eliminated by its periodic retrievals. This leaves only T_{3G} for $T_{Retrieval}$, which makes the system 4.4 times faster than the original system. When taking the ON/OFF status retrieval into account, the PIC accelerates the whole system by 8.4 times. The system performance could be further accelerated by setting the PIC to be a data pushing device, which periodically sends the power information to the server. The server can have the meters' information without waiting, which greatly improves the system's performance.

According to our experiments, when we take the longest time into account, the control center needs to wait 20 seconds to finish power information retrievals. With PIC, only one time request is require and TMetering is eliminated by its periodic retrievals. This reduction in requests leaves only time T3G for the server to retrieve power information. Because T3G is 4.5 seconds in the longest case scenario, the new PIC system is 4.4 times faster than the original system. The new PIC system is 8.4 times faster when taking the On/Off status retrieval into account.

The system performance can be further improved by setting the PIC to be a data pushing device, which means it periodically sends the power information from the meters to the control center. The control center can have the meters' power information without waiting, which greatly improves the performance of the system. One concern is that the power information is not real time data. According to our experiments, the PIC can retrieve the power information of one meter locally within

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(TEthernet+TMetering), which is less than 1 second. To finish the power information retrieval of four meters and report these data to the control center, it will take

$$T_{\text{Retrieval_PIC}} = 4T_{Ethernet} + 4T_{Metering} + 0.5T_{3G} \quad (9)$$

The time we save

$$\begin{aligned} & T_{save} \\ & = T_{\text{Retrieval}} - T_{\text{Retrieval_PIC}} \\ & = 4\left(T_{3G} + T_{Metering}\right) - (4T_{Ethernet} + 4T_{Metering} + 0.5T_{3G}) \\ & \approx 3.5T_{3G} \end{aligned}$$

Compared to the power information retrieval time of the original system, the control center could save 3.5T 3G in power information retrieval, which is 17.5 seconds in the worst case. Therefore, the data pushing system is much faster than the original system.

The self-recovered communication is implemented between the controller and the gateway by using the handshake between the server and the controller. When the controller loses the handshake for 5 minutes, it will reset its serial port related registers to recover the communication. Also, if there is no EV charging for 1 hour, the controller will reboot itself to keep alive the communication between the server and the controller. The reboot mechanism of the controller is done by using Watchdog feature.

3.7. Integration with Commercial Chargers

3.7.1. Level 1 Charging System Integration

The level 1 multiplexing EVSE for current implementation consists of a box with four outlets attached to the outside where customers can plug in the 120V EV portable trickle-charge cable. Above each of the four outlets, there is an indicator light that indicates which outlet is provided power. There is a fifth light that indicates whether or not the charging box has power and is in service. Inside the box, there are four relays with metering capability that both turn the power on and off to each outlet and measure the current to ensure that the device is truly off. A router inside the box communicates between relay/meters and the control server.

The main function of multiplexing is to share the available power among multiple EVs. Since the level one EVSE does not communicate directly with the EV, the amount of power that an EV pulls cannot be controlled. Therefore, to ensure that the circuit does not overload, the control algorithms dictate that only one EV (at a time) can charge per circuit. A redundant system first turns off the power to any charging EV, and then checks the current flowing through each relay to ensure that no current is flowing before proceeding to engage power to the next EV in the queue. This redundant system ensures that the circuit is never overloaded. Because software controls turning off and on the charging, many different algorithms can be explored for scheduling the EV charging. These algorithms can take into account time of arrival,

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state of charge, end time of charge, grid stability, price and any other factor relevant to EV charge scheduling.

3.7.2. Level 2 Charging System Integration

The multiplexing J1772 EVSE must incorporate all the J1772 standards, cables, and protocols. In addition, it must connect multiple EVs at once and safely provide optimal charging. To accomplish this, the J1772 charging device incorporates all of the capabilities of the trickle charger including the communication router, four relays for control power and electrical metering. Furthermore, it includes systems that communicate with the EV to let the EV know it is connected and how much power is available; shut power off if the cable is disconnected; and provide ground fault protection (GFCI) capabilities that shut power off if a fault is detected. A picture of a deployed J1772 multiplexing EVSE charging multiple EVs at once is shown in Figure 100.



Figure 100. Level 2 J1772 EVSE

With the average commute of 12.6 miles [20], and a Nissan Leaf getting 29kWh/100mi [21], the energy required to recharge the EV after the average commute is 3.7kWh. A dedicated, 30A (40A peak), 240V circuit supplying a level 2 charger can supply 7.2kW of power, which will translate into 6.6kW going into the battery after inefficiency losses. In this scenario, the average commuter's EV can be recharged in a little over ½ an hour. With four EVs sharing the circuit, it only takes two hours to recharge all the EVs. If the average commuter will stay at work for 8 hours, the circuit will provide much more power than what will be require to satisfy the customer. Not all situations have the same criteria; therefore, in order to optimally serve the customer's requirements within the limits of the grid resources, both EVSEs can be configured to work with different constraints depending on the available grid resources and charge

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requirements. A few scenarios will demonstrate the flexibility with which this system can be configured to suit a given situation.

Installations at malls or other public places where the commute may be longer than average and the EVs may be parked for shorter periods of time; sharing a 30A circuit may not fulfill the customer's requirements. If the level 2 EVSE has a 120A circuit, all four EVs can charge at full 30A each. If many chargers with this setup are connected to a single transformer, than the transformer could be a bottle neck. If each EV charges at 7.2kW, then a 100kVA transformer can handle a maximum of thirteen charges. In this scenario, a group of four or more EVSEs, with sixteen or more charge points can charge the first thirteen EVs that arrive at maximum charging speed. The control system can run algorithms that limit the power consumed by the EVSEs as a group by putting the 14th EV into a queue or lower the power allotment for the other EVs to provide power to the 14th.

If splitting1.5kW (120V, 12.5A) four ways with the level 1 EVSE does not satisfy the given set of power requirements, then the EVSE can be configured to split two 120V circuits between the four charge points. This leaves each circuit to be shared by only two plug points averaging 0.75kW each. If a 1.5kW level 1 circuit is too much power for four EVs, such as at airport parking lots where EVs may stay for long periods of time, multiple EVSEs may be safely connected to one circuit. The average charge required will determine the optimal number of EV plug points for a circuit. A 1.5kW circuit can deliver 36kWh/day and 252kWh/wk. Since a Nissan Leaf's batter capacity is 24kWh, a 1.5kW circuit can charge twenty-one half discharged Leafs in a week. If the average parking time is a week, connecting twenty charge points per circuit would be appropriate. This would allow a very large number of EV charge points to be installed without major infrastructure upgrades, just a system configuration. The current implementation includes many level 1 trickle chargers with four charge points connected to one circuit. It also includes a number of J1772 chargers, some sharing 1 circuit between four EVs, others sharing two circuits between four EVs.

3.7.3. Implementations of Integration with Commercial Chargers

The smart charging infrastructure can be achieved by installing the metering system on simple charging stations, like those from Leviton, ClipperCreek, and Schneider, so they can be directly controlled by switching type algorithms – such as round-robin and fair charging algorithm – run on the server.

There are two types of simple, off-the-shelf, commercial charging stations with or without dedicated current switching options: Dedicated Current Switching and Variable Current Controlling. In the current switching method, the commercial charging station provides terminals inside the charging station for the installer to throttle the current. Stations without the switching current option can be added to the infrastructure using a controller with Variable Current Control.

As previously mentioned in the Current Switching case, the installer can use terminals inside commercial charging stations to throttle the current. For example, the output current of ClipperCreek CS-40 model can be changed based on terminal connections. Changing connections between terminals permits selecting three stages of current: 30A, 6A, and 0A. Switching current on multiple charging stations in a locale has a communication cost, which can be reduced using a ZigBee mesh network solution with relays

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implemented. Figure 101 and Figure 102 show the implementation of these two types of controllers using Texas Instrument CC2530ZNP.

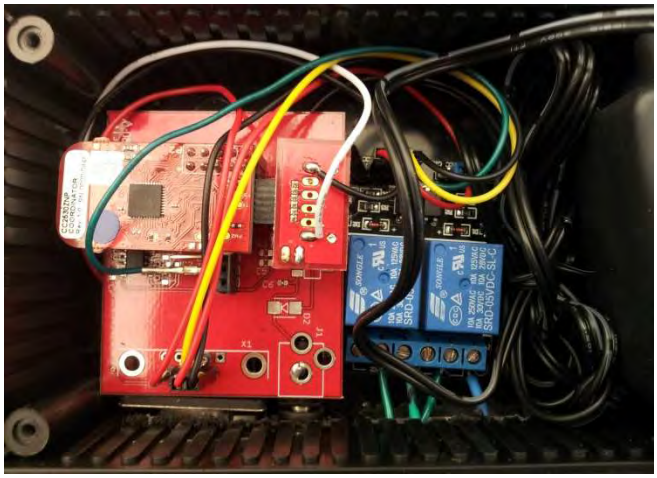


Figure 101. ZigBee Coordinator Type Controller

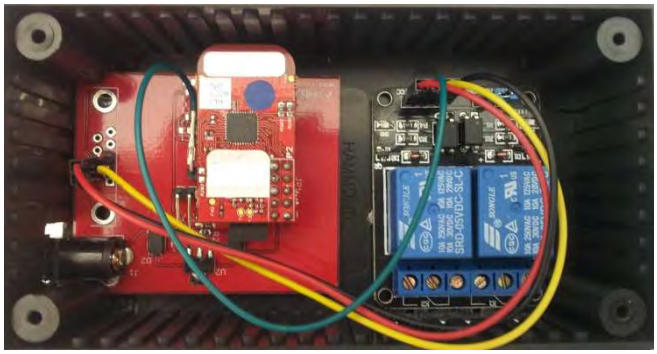


Figure 102. ZigBee Router Type Controller

Both controllers switch relays on and off to control the connection of the terminals inside the charging stations upon receiving the command from the server to change the output current.

In order to send commands to the corresponding controllers, the ZigBee coordinator must associate the routers' unique MAC addresses and their dynamic IDs. The MAC addresses on server commands are used by the coordinator to look up corresponding dyanmic IDs on the joining list of routers to pass commands to the appropriate routers. To ensure a robust network connection with each ZigBee device, the coordinator and routers use a handshake protocol. Figure 103 and Figure 104 show the firmware flow of the ZigBee coordinator and the ZigBee router in the MSP430 of CC2530ZNP.

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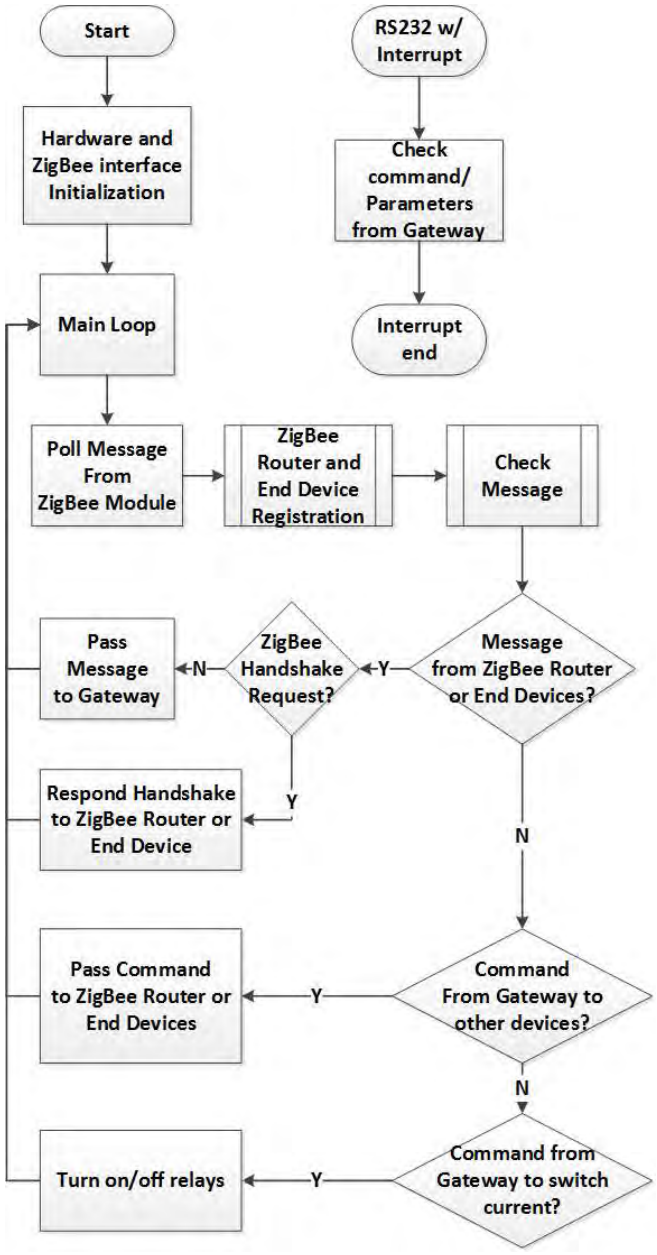


Figure 103. ZigBee Coordinator's Firmware Flow [51]

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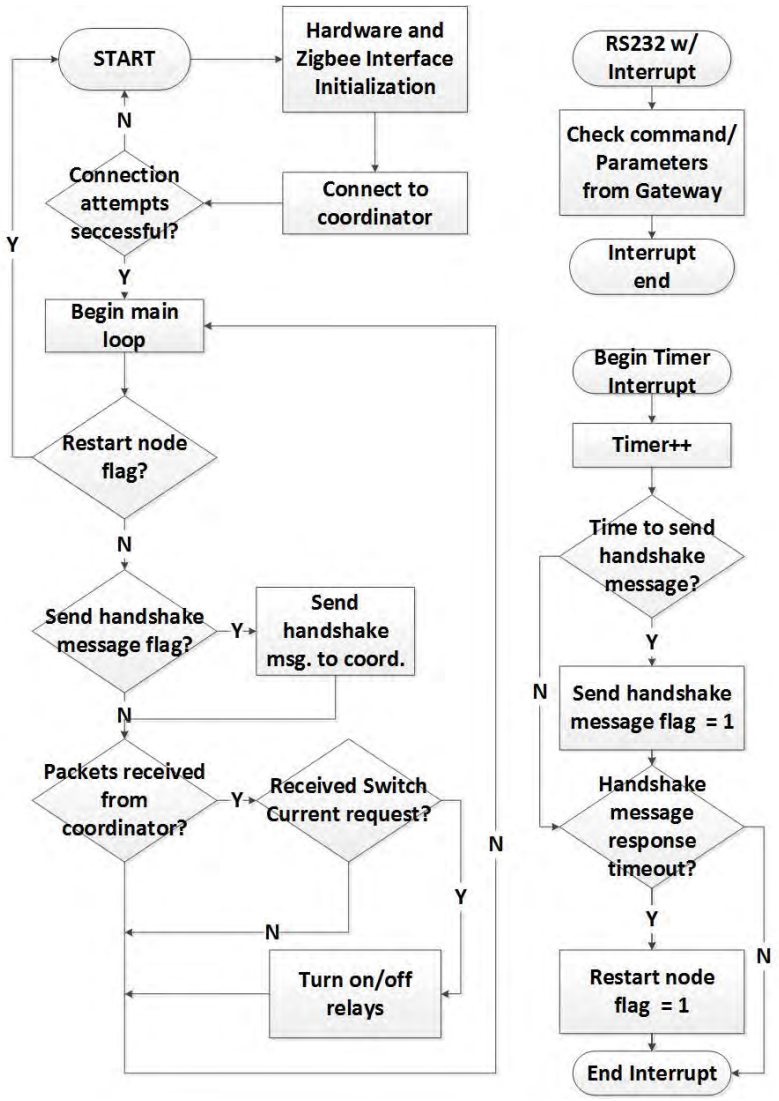


Figure 104. ZigBee Router's Firmware Flow [51]

The control box houses a gateway, meter, and controller as shown in Figure 105.

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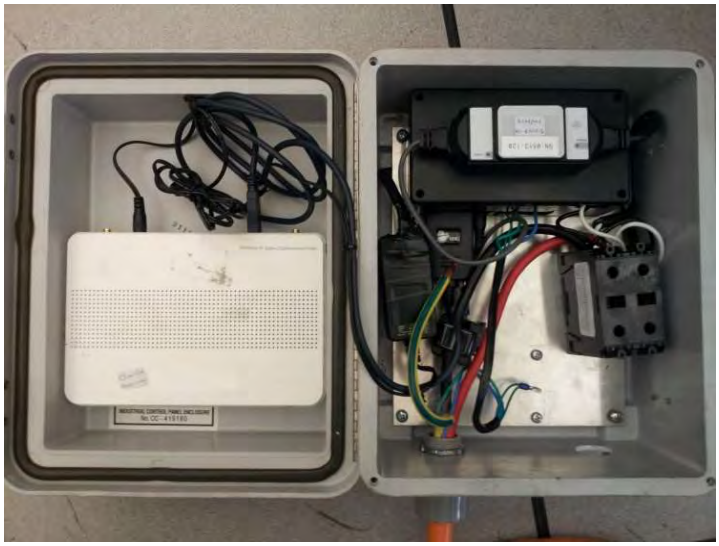


Figure 105. Control Box for ClipperCreek Charging Station

Figure 106 shows a controller box installed on a ClipperCreek charging station.



Figure 106. Installation of a smart ClipperCreek Charging station

Simple commercial charging stations without the switching current option can join the infrastructure using a controller with Variable Current Control. To implement a variable current control on these stations, without violating GFCI safety requirements, requires an extra circuit because simple charging stations incorporate the J1772 standard, which requires them to control relays and the duty cycle of the pilot signal when connected to a PEV; the relays are used to turn the PEV on and off and the duty cycle rates the power that the PEV draws. Therefore, to respond to server commands, the circuit must emulate the behavior of a PEV and generate a pilot signal with variable duty cycle, as shown in Figure 107.

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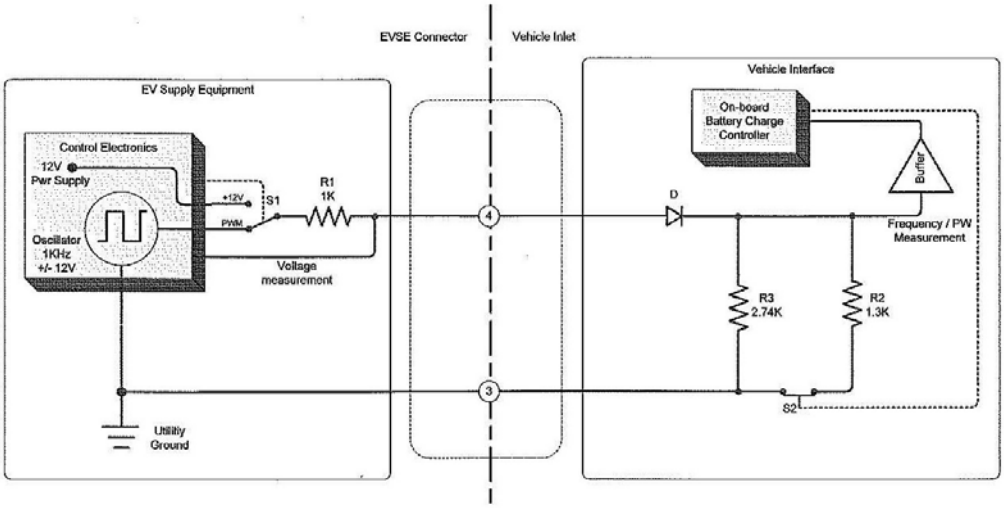


Figure 107. Pilot Signal Connection in J1772 Standard

Figure 108 shows the implementation of the Variable Current Control type of controller.

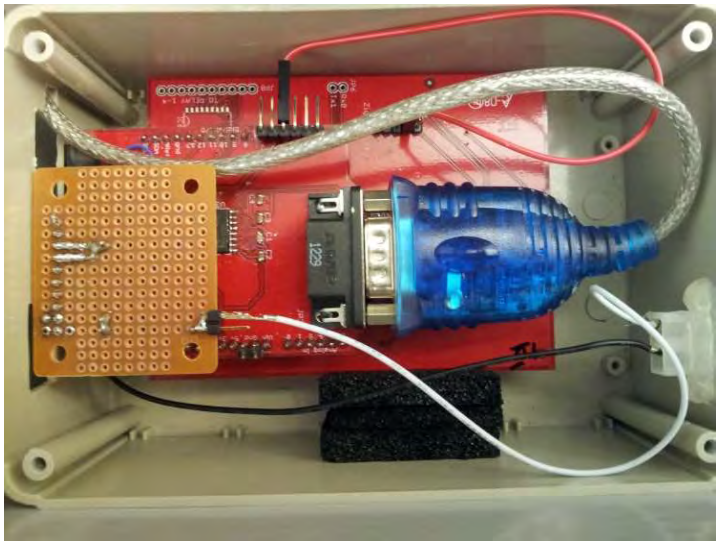


Figure 108. Variable Current Control Type of Controller

Unlike the Current Switching Method, the interface between the charging station and the PEV is the controller, which consists of two components: Pilot Signal Generator/Monitor and PEV emulator. The Pilot Signal Generator/Monitor generates the pilot signal for the PEV, while the PEV Emulator emulates the PEV's response to the original pilot signal generated by the commercial charging station; the emulator consists of a diode, two resistors, and two Darlington transistors acting as the switch. Figure 109 shows the schematic of the EV emulator and Figure 110 shows the state machine flow.

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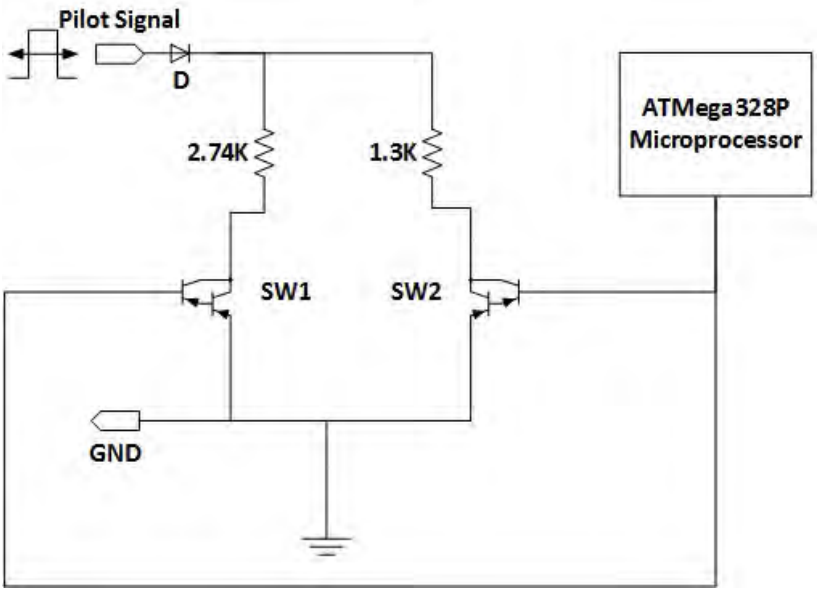


Figure 109. Schematics of PEV Emulator

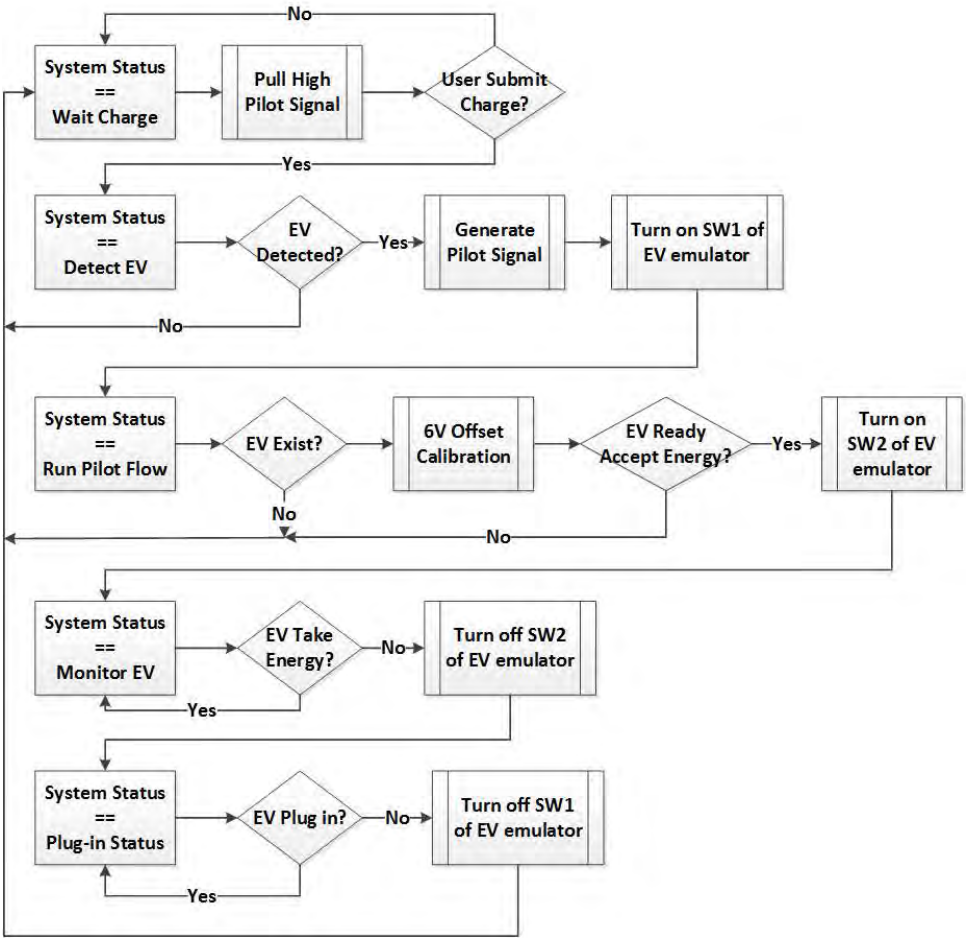


Figure 110. State Machine Flow in the Firmware

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Similarly to the previous Current Switching controller type, the Variable Current Controller also comprises a gateway, meter, and control unit as shown in Figure 111.

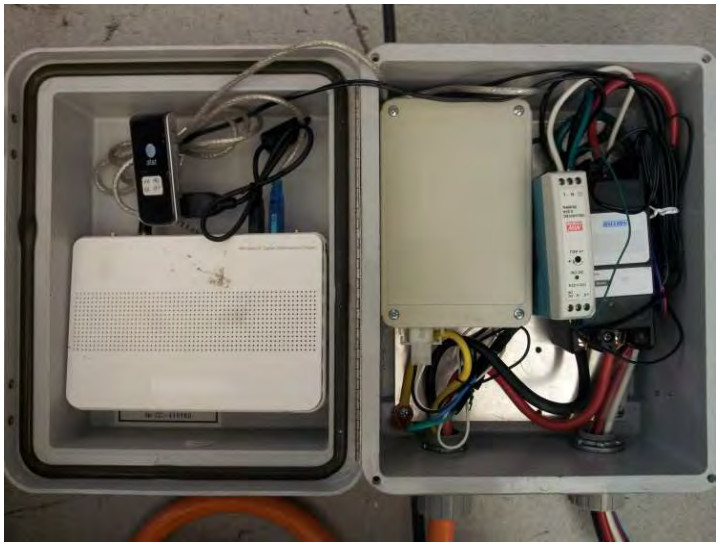


Figure 111. Control Box for Schneider Charging Station

As we see, by adding an additional controller, a commercial charging station can join the PEV charging infrastructure with the capability to remotely monitor and control variable currents. Figure 112 shows the implementation of the control box, and Figure 113 shows a demonstration with a Nissan Leaf.

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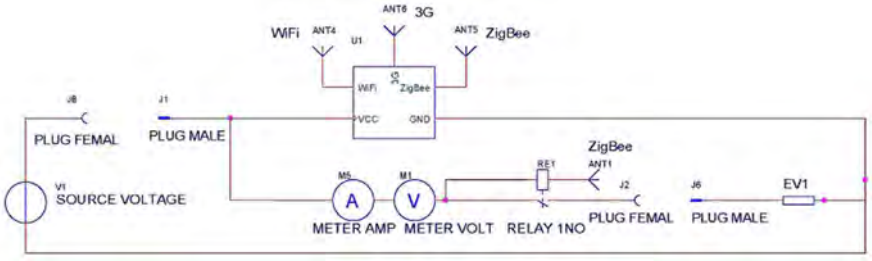


Figure 112. Implementation of smart Schneider Charging Station



Figure 113. Demonstration with a Nissan Leaf

The metering system only requires a gateway and a meter as shown in Figure 114.



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Figure 114. Schematics of the Metering System.

3.8. PQA and PMU Integration

3.8.1. Introduction of PQA and PMU

Electric power distribution systems in the past involved primarily in distributing unidirectional energy with a relatively low voltage. It was simply unnecessary for close monitoring and neither economically viable to preserve high level of observability. However, the growth of distributed energy resources (DER) such as photovoltaics (PV) and windmill, electric vehicles (EV), distributed storage system (battery) and smart grid applications like automated demand response turned distribution grid from a passive energy provider into an active energy producer. This growth adds uncertainties and even potential risks to the distribution system. However, it also brings opportunities for better utilization of energy. To better observe and understand its dynamic essence, to perform better control application, and to better capture the merits of DER and smart grid applications, we plan to implement Power Quality Analyzer (PQA) and Phasor Measurement Unit (PMU) in UCLA distribution network, and to study its potential diagnostic and control applications.

For PQA, it measures the power quality information such as active/reactive power, frequency and power factor. Besides the above mentioned basic power quality measurements, it also provides insight on frequency domain analysis, harmonic analysis and potential power quality evaluation. PMU measures the phase angle of different nodes in a power grid with GPS. It provides the possibility of monitoring the phase angle deviation of the power grid. Fast charging with large power consumption and solar power injection may have observable impact on distribution grid. With PMU such impact could be more precisely captured, and together with PQA, the overall status of the distribution system could be better understood and corresponding actions could be taken to preserve its health.

Implementing PMU in UCLA will have a twofold benefit.

To begin with, there have been several research labs nationwide that works on PMU application in distribution system and thousands of publications on this matter. In California, a project consisting of CIEE, Power Standard Lab, UC Berkeley, Lawrence Berkeley National Lab and lead by Professor Alexandra von Meier dedicated in micro-synchrophasor applications for distribution system is on the run [22], [23]. Several dozens of diagnostic, planning and control application has been proposed and some of them are more promising and practical than others. For instance, PMU facilitated distribution system state estimation has been widely studied [24], [25]. Traditional state estimation take advantage of real and reactive power flow and form into a nonlinear problem that use Newton-Raphson method to solve iteratively for a solution. However, PMU measurement provide a direct measurement of the system state (consisting of voltage magnitude and phase angle), which greatly simplifies the solving process and increase the accuracy. Also, PMU could be used in islanding detections [26], [27]. Islanding detection methods could be generalized into different categories based on standard chosen. PMU based islanding detection could be seen as a communication based islanding detection. Although it usually comes with high cost, communication based islanding detection is generally grid friendly.

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In UCLA, power consumption of a general situation is around 50MW, with 35MW produced locally and 15MW buying from utilities. The peak load, however, could reach as high as 70MW. The total amount of power combined by PV and battery systems are around 100kW. Despite the fact that this is still a small figure compared to the 50MW, the penetration of PV will keep going up and reach the size of megawatts. High penetration of combination of PV/battery storage system/EV fleets has not been widely studied for its dynamics nature, and we believe UCLA would be the perfect test bed for its growing PV size, over 100 EV chargers of different levels, with a peak load of 140% of normal generation. And PMU with highest accuracy and sample rate among monitoring device (for some specific dedicated device this may not be true) would make sure no potential risks are neglected due to low sample rate or accuracy. Therefore, implementing PMU is not just valuable in the sense research but also in the sense of engineering.

3.8.2. Current Realization of PQA and PMU

Starting from April 2015, basic configuration of PMU/PQA has been done and awaits green light from UCLA and the first set of PMU/PQA has been installed in January 2016. We have two sets of PMU/PQA in total. Currently, one set of the PMU/PQA has been transferred and installed in parking structure 9 (PS 9), monitoring a Lv.1 charger. PS 9 will have a large PV system installed recently. This PMU/PQA will stay at PS9 after the PV being installed (with construction already began) to provide data for a before/after analysis of PV installation. Another set of PMU/PQA is planed to be installed in PS 3 on a Lv. 2 charger that is able to split its current. We plan to gather data of one splited tunnel and the main to capture their difference.

We have designed the PQA and PMU using the National Instrument's (NI) CRIO reconfigurable FPGA platform. The PQA and PMU collect and display real-time data, and send the data to MySQL database through HTTP protocol. The data is then collected by the super control center (SCC) for integrated display and monitoring. The PMU also sends data to the ePDC™ software, which will be introduced later.

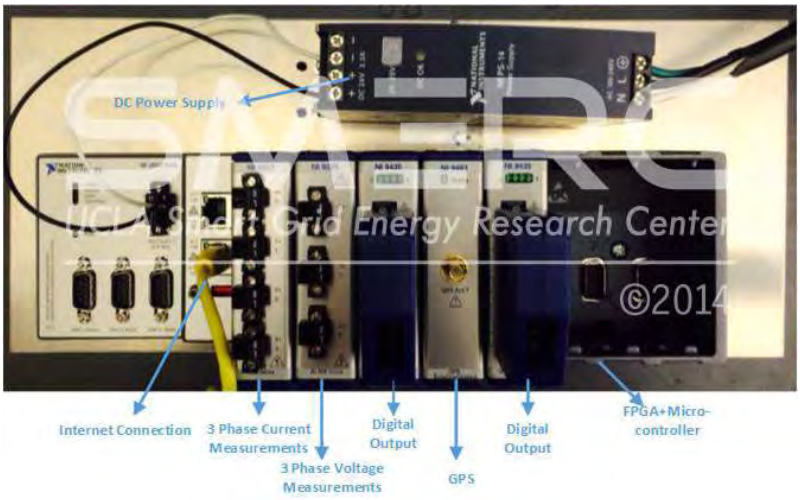


Figure 115. PQA and PMU hardware

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Figure 116. GPS Antenna

On the PQA and PMU implementation side, NI's CRIO is selected as the hardware platform, as shown in Figure 115. The reasons we chose NI as the primary PQA and PMU development environment are its high reliability, modest physical size and fast-prototyping characteristic. In the figure, important components including the CRIO micro-controller, current and voltage sensors, and GPS modules are marked out. The hardware will be programmed in LabVIEW, NI IDE software, to provide PQA and PMU functionalities. The program will be compiled and downloaded to the hardware via an Ethernet connection. The GPS antenna in Figure 116 has a gain of 27dB ± 4dB, which is enough to accomplish the synchronizing task.

Figure 115 shows the PMU/PQA configuration for indoor experiment. For outdoor installation, a change of configuration is necessary. In Figure 117 the configuration is shown. In Figure 118 and Figure 119 its installation location is shown. The PMU/PQA sits in between an AC EV charger and the power grid, and monitors the power flowing into the charger. Voltage input comes directly from the power source and current input comes from a Magnelab current transformer with a maximum current input of 200A. This is sufficient for most of the level 3 chargers. PMU/PQA is powered by a NI 24V DC power supply. Due to the inaccessibility of wired network, two Billon 3G gateways are added to transfer data. NI hardware requires global static IP to communicate and therefore both gateways are configured with port mapping to enable this access (see Figure 120). Since both the NI hardware forward same ports, two routers, or one router with two chips are needed. In this case, we simply configured both of the routers. The gateways are powered by a 12V DC power supply. The whole box is waterproof. Upon installation, small changes are made by the UCLA construction team on the power entrance and exit. As shown in Figure 119, power comes in and goes back to the charger through the same tunnel. From Figure 120 to Figure 123 show the configuration of communication and data is sent to the super control center for integrated data visualization and monitoring.

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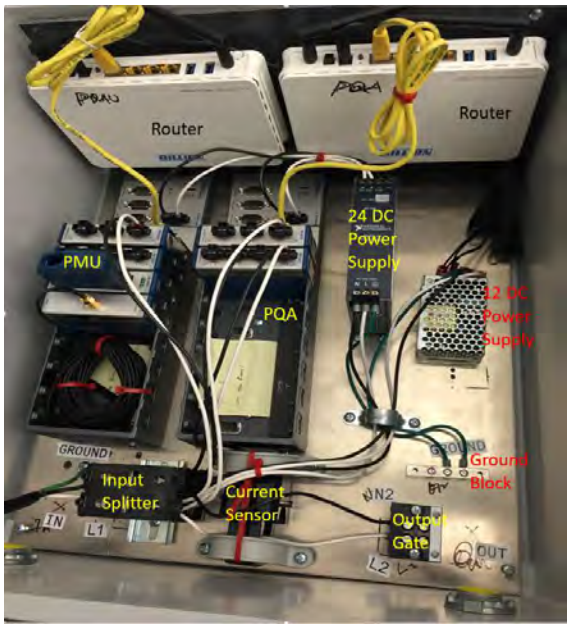


Figure 117 PMU/PQA Configuration for outdoor installation



Figure 118 PMU/PQA Box at parking structure 9

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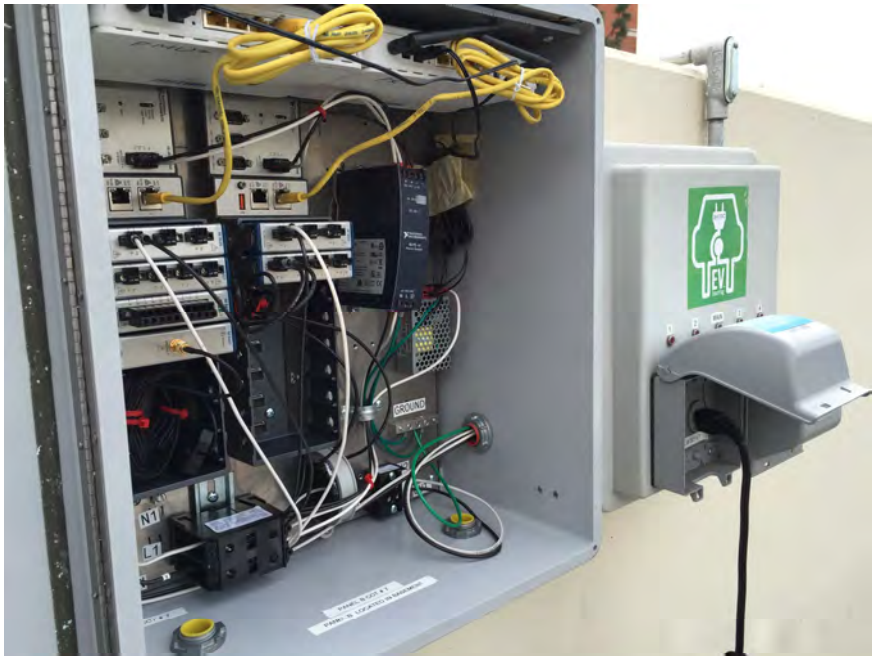


Figure 119 Closer look of PMU/PQA installation site

Add | Edit / Delete

Edit	Application	Protocol	External Port	Internal IP Address	Internal Port	Time Schedule	Delete
	FTP	TCP	21~21	192.168.1.185	21	Always On	
	PMU1	TCP	20~20	192.168.1.185	20	Always On	
	HTTP	TCP	80~80	192.168.1.185	80	Always On	
	PMU2	TCP	81~81	192.168.1.185	81	Always On	
	PMU3	TCP	2343~2343	192.168.1.185	2343	Always On	
	PMU4	TCP	3079~3079	192.168.1.185	3079	Always On	
	PMU5	TCP	3537~3537	192.168.1.185	3537	Always On	
	PMU6	TCP	3580~3580	192.168.1.185	3580	Always On	
	PMU7	TCP	44516~44516	192.168.1.185	44516	Always On	
	PMU8	TCP	44525~44525	192.168.1.185	44525	Always On	
	PMU9	TCP	51700~51700	192.168.1.185	51700	Always On	
	PMU10	TCP	57616~57616	192.168.1.185	57616	Always On	
	PMU11	TCP	59110~59110	192.168.1.185	59110	Always On	
	PMU12	TCP	62602~62602	192.168.1.185	62602	Always On	
	PMU13	TCP	8000~8000	192.168.1.185	8000	Always On	
	PMU14	TCP	3581~3581	192.168.1.185	3581	Always On	
	PMU15	TCP	3582~3582	192.168.1.185	3582	Always On	

Figure 120 Router port mapping



Figure 121 Checking connections

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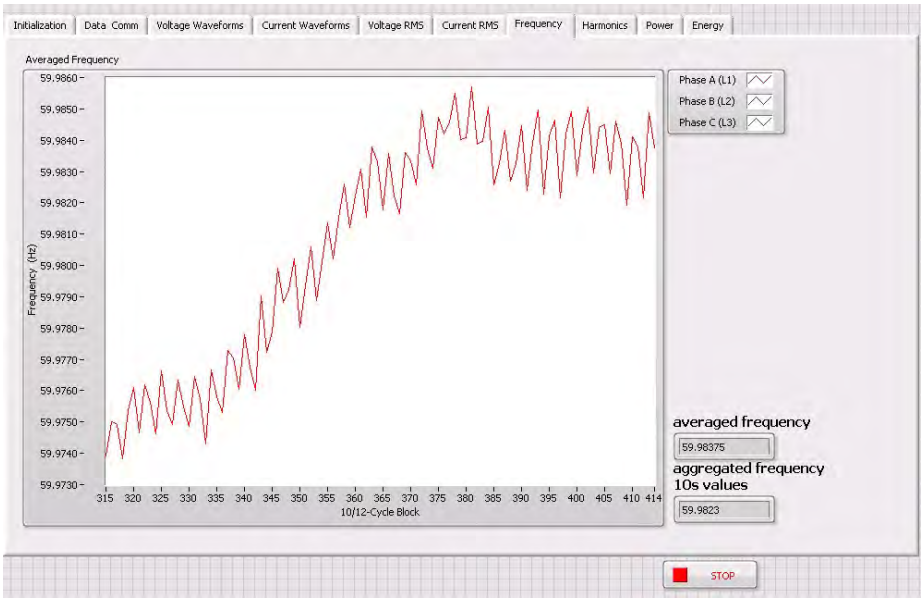


Figure 122 Test of data visualization on LabVIEW on a one phase load



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Figure 123 Data Stored in MySQL database (same load as in Figure 122)

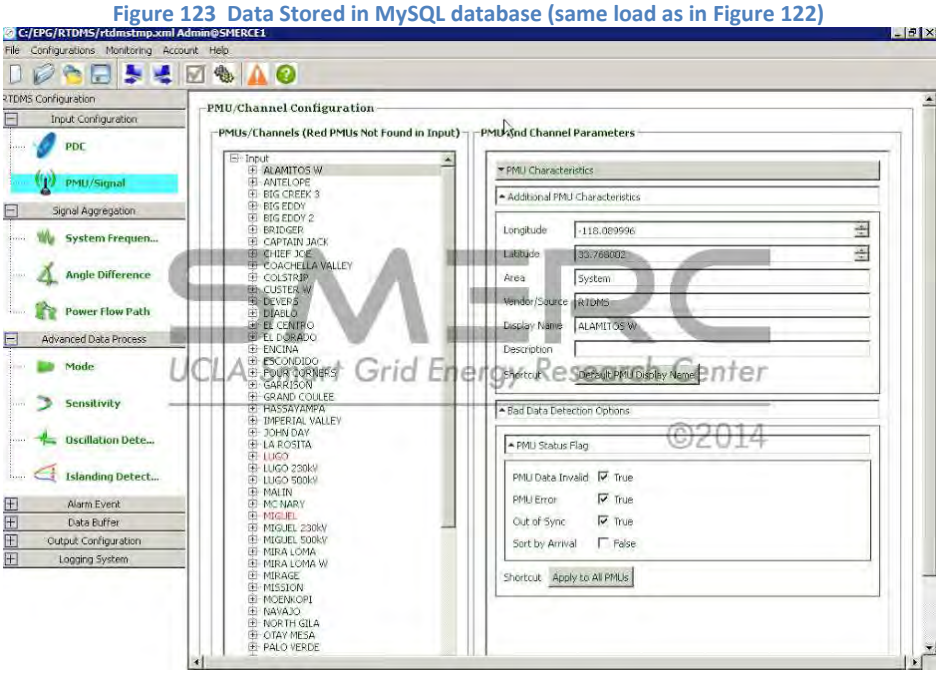


Figure 124. RTDMS software interface

On the real-time software side, Real Time Dynamics Monitoring System (RTDMS) from Electric Power group (EPG) is used as the monitoring system, as shown in Figure 124. A preliminary literature research has been done to understand the existing market of real-time monitoring management software systems. Compared to traditional systems that provide static estimations derived from model based computations, RTDMS [28] is a powerful synchrophasor software application for providing the capability to monitor in real-time and analyze the dynamics of the power system. In addition, RTDMS can monitor the critical metric of grid dynamics, like phase angle differences, small signal stability (oscillations & damping), frequency instability, generation-load imbalances, power-angle sensitivity and power-voltage sensitivity.

3.8.3. EPG software integration with NI hardware

Power monitoring software ePDC™ from Electric Power Group has also been installed (see Figure 125). The software has been set up to connect to the PMUs that measure the real-time power quality of the EV charging system. The three-step installation process of ePDC required us to configure the data manager, the input PMU system, and then monitor the results. Data will be stored in database and used for analysis, which is introduced below.

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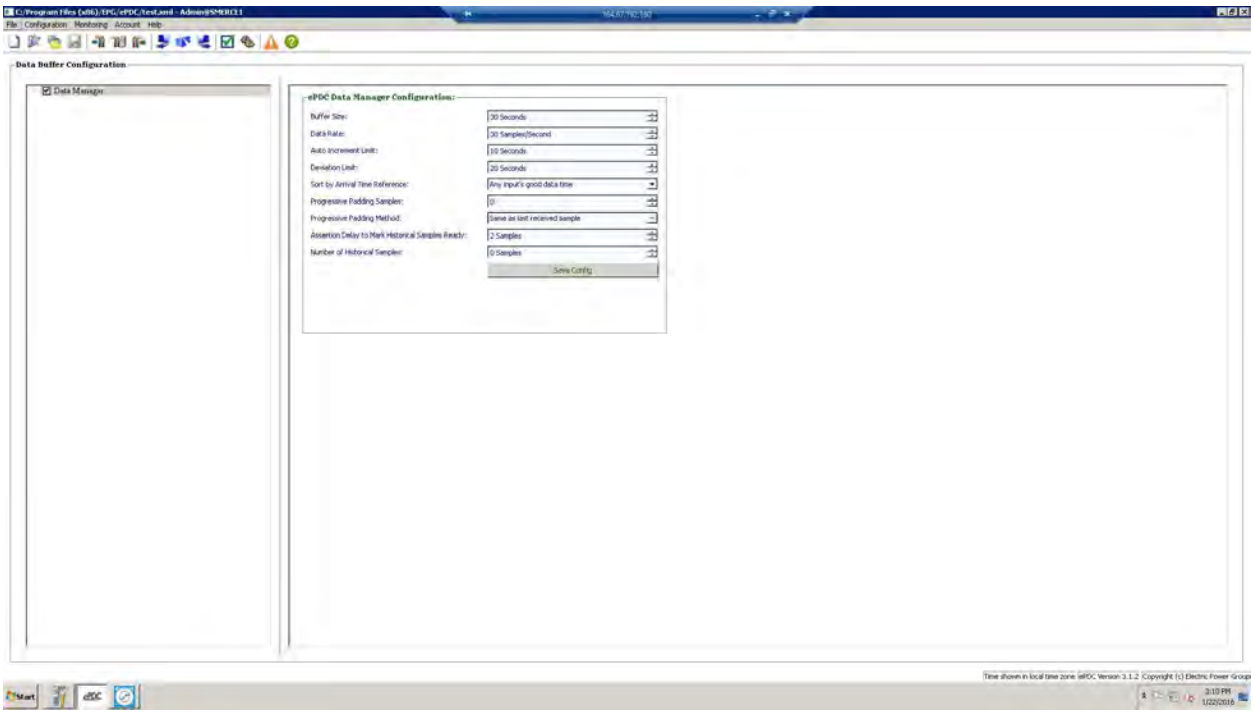


Figure 125. EPG software interface

3.8.3.1. Data Manager

The data manger's configuration allows users to configure various parameters including the buffer size, data rate, auto increment limit, deviation limit, sort by arrival time reference, progressive padding samples, progressive padding method, assertion delay to mark historical sample ready, and number of historical samples. We used the section's default values because the PMU that is already installed on-site does not have any special requirements.

3.8.3.2. Input Configuration

This section involved selecting the communication type and data formats, as well as create the system configuration of the PMU as an input device. In addition, we also had to input the IP address and port number of the PMU that will be connected. There were no compatibility issues, because the PMU uses the TCP protocol and the C37.118 data format that are both compatible with the ePDC software. We also created a "test" project to connect to the installed PMU in order to validate the system. Figure 126 shows the main page of the input configuration section and Figure 127 shows the details of the "test" project, including the options for communication, PMU data processing, and PMU characteristics.

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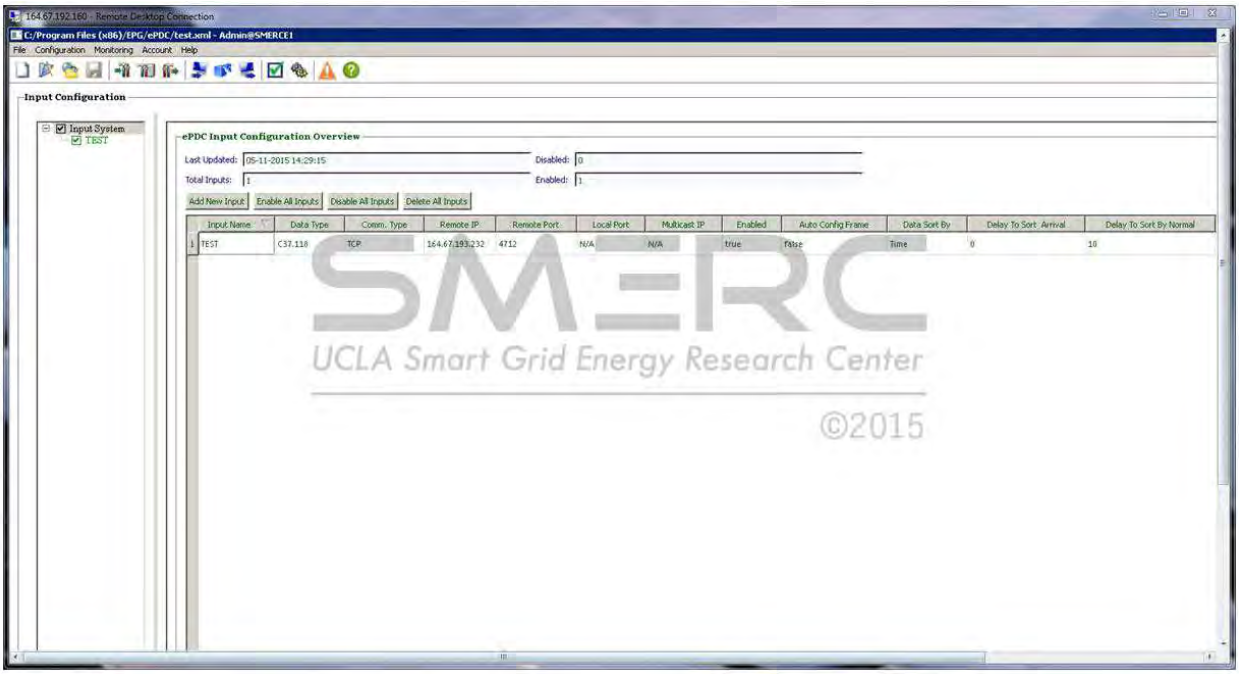


Figure 126. Screenshot of Input Configuration Main Page

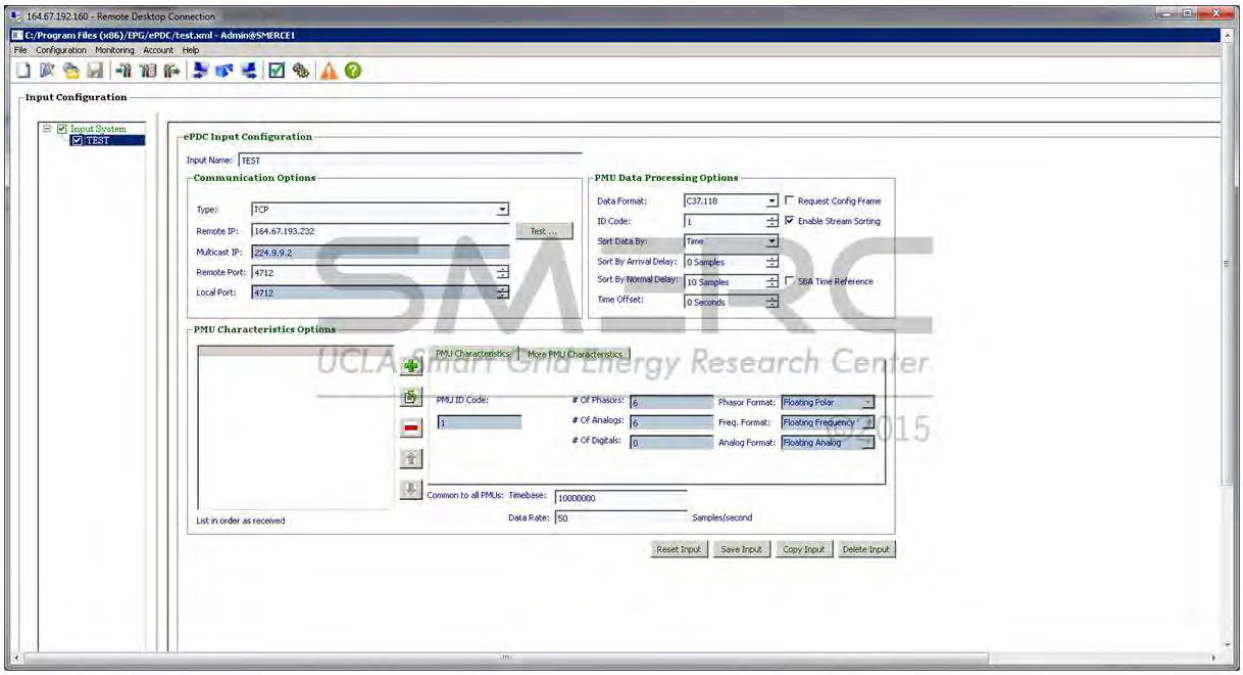


Figure 127. Screenshot of Input Configuration Detailed Page

Monitoring Result

In order to monitor, the ePDC software connects to the PMU via the IP address and port using the C37.118 format. The software then begins to receive the real-time data including three-phase voltage and current,

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and frequency. The ePDC displays the results on the output page along with a real-time chart showing the plotted information.

Figure 128 shows the main page of the ePDC's monitoring section that provides a summary of the status of the inputs, including the number of the PMUs that are connected and whether they are active or not.

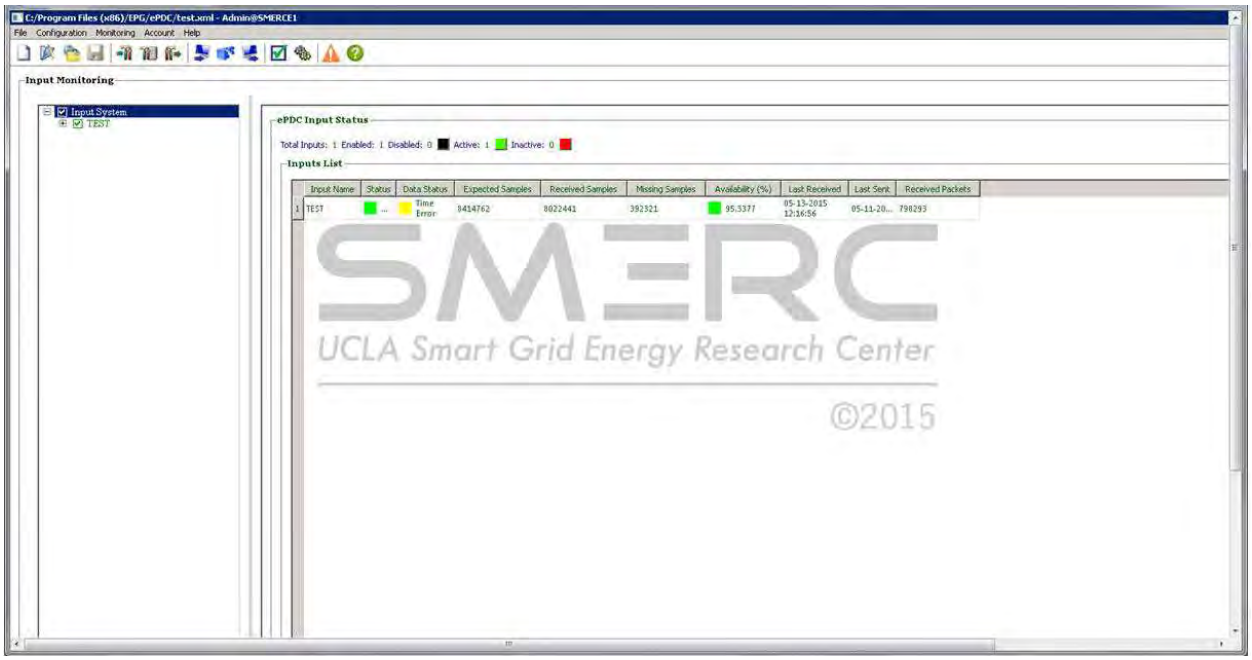


Figure 128. Screenshot of Monitoring Main Page

Figure 129 shows the details of the monitoring results for the PMU that was connected in the "test" project, including the real-time value of the three-phase voltage, current and frequency. Figure 130 shows the plots of the real-time monitoring results.

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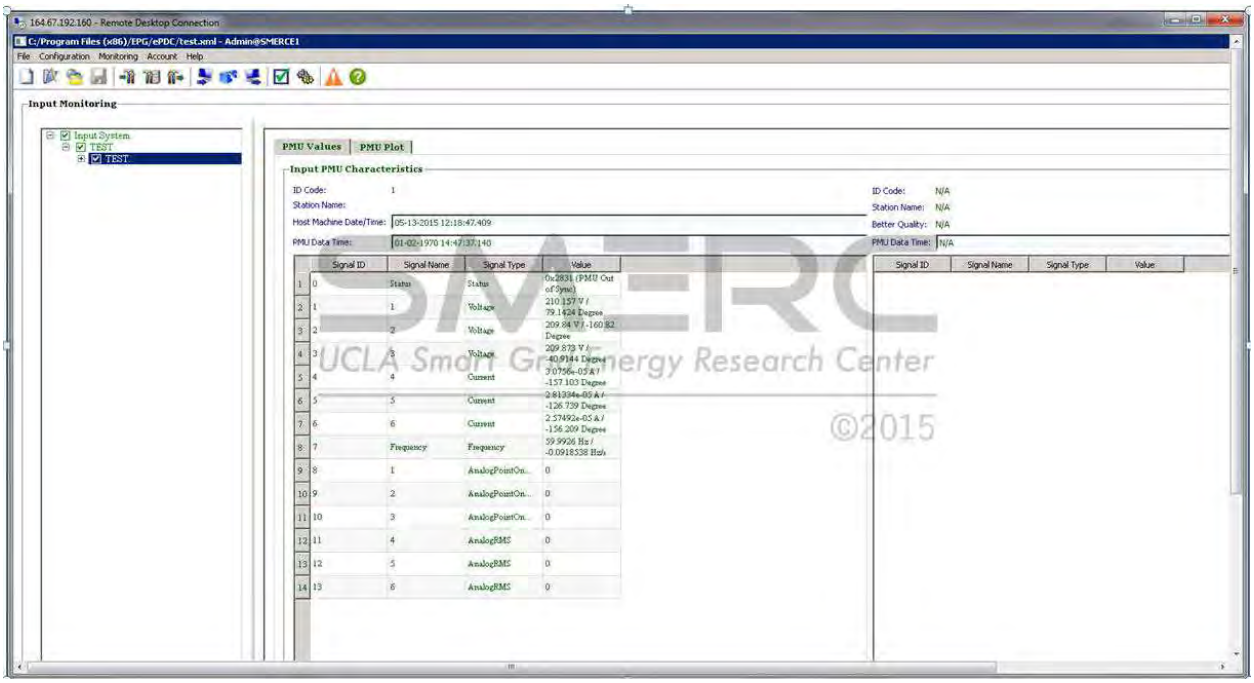


Figure 129. Screenshot of PMU values monitoring page

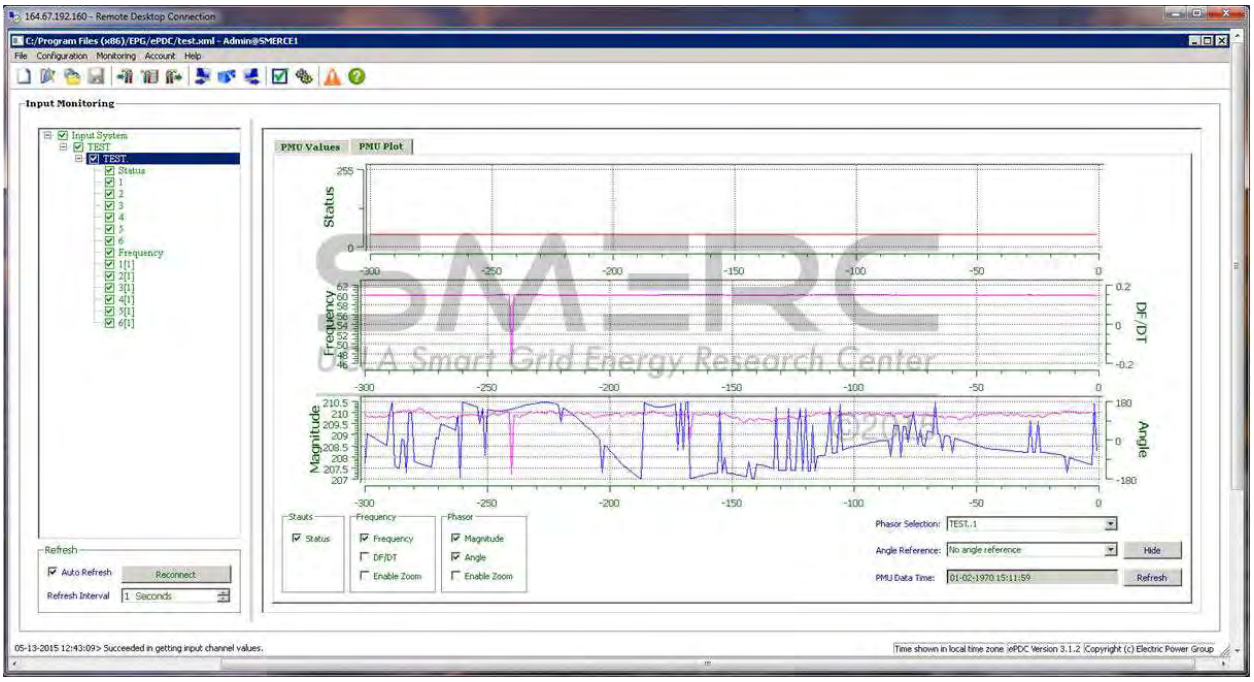


Figure 130. Screenshot of PMU plot monitoring page

3.8.4. Research and Development issues

The PMU/PQA box has started to gather data on Lv.1 charger in PS 9. We want to perform a thorough study of the capability of PMU/PQA so we start with a one phase device. After 3-4 months (Depending on the schedule of PV construction mentioned in 3.8.2) of data gathering, this PMU/PQA will be installed

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back to the three phase battery storage system (see Figure 131). We are also in stall PMU/PQA on PV systems, Lv. 3 charger (see Figure 131) and V2G device. Data gathered on different devices will be stored and compared to provide useful information on the value of data measured by PMU and also hints on PMU placement in distribution grid. Eventually, the ideal case is we have 4 to 5 PMU sitting on different high voltage/current device and monitor their effect to the entire UCLA microgrid. Under such scenario, PMU data will explored for applications including distribution system state estimation and islanding detection.



Figure 131. The application of PQA and PMU

PQA will provide ample information of the power quality, and PMU will give out a direct measurement of the system state, which facilitates diagnostics applications like islanding detection and state estimation. The phase angle given by PMUs in different physical locations also provide information of the grid healthiness. With integration of PMU/PQA into the monitoring system, we believe a better knowledge of the distribution grid with increasing penetration of DERs will be gained and with such knowledge the uncertainties brought by such growth could be countered, and merits of DER/smart grid applications could be optimized. At this moment, no one knows what would be captured by these high accuracy devices and the only way to figure out is to install them and start gathering data.

3.9. Status of Charge (SOC)

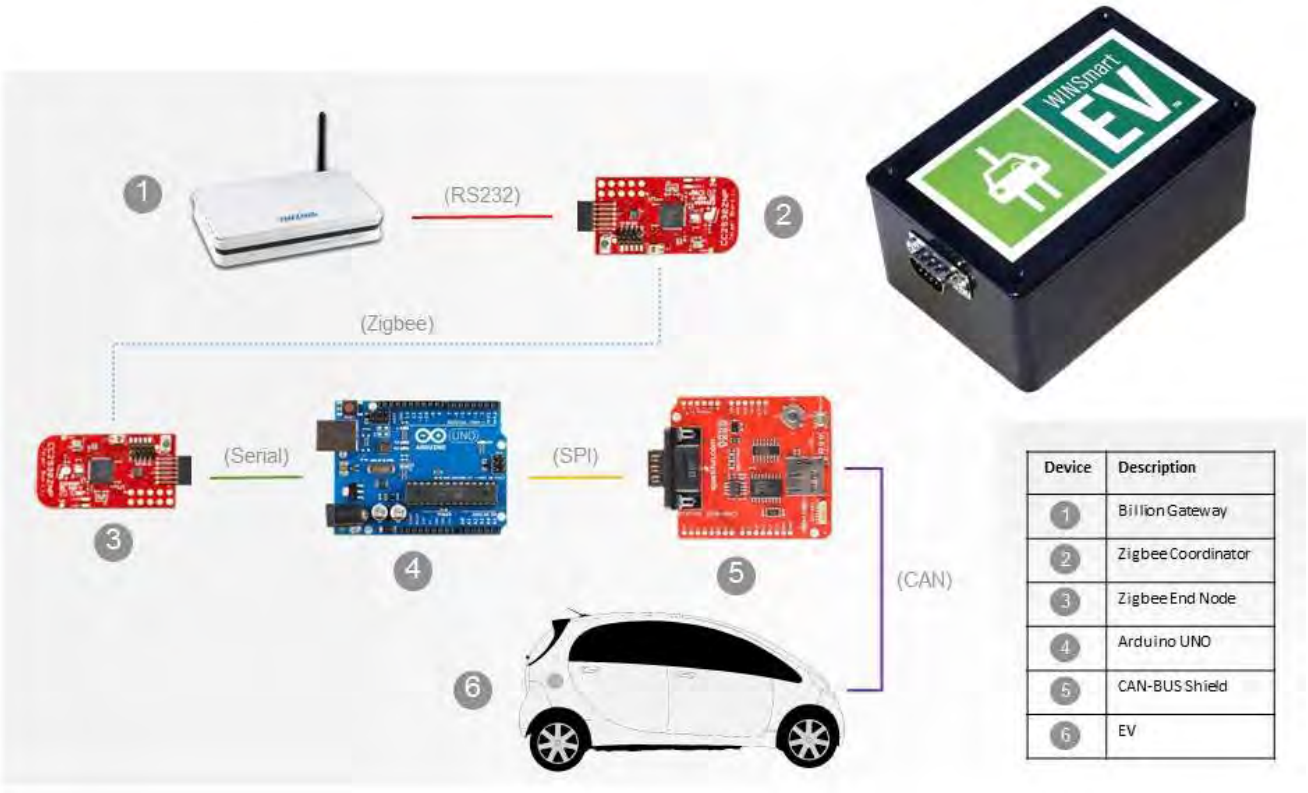
In order to optimally schedule charge intervals of multiple vehicles, as well as provide EV owners with real-time charge data, the state of charge of each EV must be known. The latest EVs, unfortunately, do not have provisions that allow the State of Charge to be retrieved by third parties. Some companies provide web interfaces that feature very approximate charge states or values that are derived from the charge state, such as range. This is not enough. Therefore, a way to retrieve SOC must be developed before auto manufacturers develop a common standard for vehicle to grid communication. The Zigbee Enabled Electric Vehicle State of Charge Remote Meter presents such a workaround. It allows the state of charge data to be accessed remotely via Zigbee link. The data may then be used by a charge scheduling algorithm or by the EV owner for monitoring.

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The SOC meter is based around an Arduino microcontroller platform with a CAN-BUS shield. For wireless communication purposes, the Arduino and shield are paired to a Zigbee node. This device is located inside each vehicle that is to be monitored.

Another device is located inside the charging station. It serves the role of coordinator and is able to communicate with each of the end nodes individually by sending packets to their specific MAC address. This is the same device that is used to send commands to the pilot signal generator circuit in the new SMERC Level 2 charging boxes. Therefore, the SOC meter is compatible with the existing and to-be-installed hardware.

The most important point about the way in which the SOC is retrieved is that a command must first be issued from the charging controller side to the SOC meter before the meter will respond with the current SOC value.



Device	Description
1	Billion Gateway
2	Zigbee Coordinator
3	Zigbee End Node
4	Arduino UNO
5	CAN-BUS Shield
6	EV

Figure 132 - Communication diagram

In order to provide State of Charge data, the following sequence of operations takes place:

1. The user issues a URL command to the Billion gateway [1].
2. The command is passed to the Zigbee coordinator node[2] via RS232

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3. The coordinator node checks the format of the command and, if correct, passes the command on via Zigbee to the end node [3]. Each end node addressed with its specific MAC address, so multiple end nodes can be on the network simultaneously.

4. Once the end node[3] receives the command, it checks the command format and, if correct, passes a command in the form of a key word via Serial bus to the Arduino [4].

5. As soon as the Arduino receives the key word from the Zigbee end node, it begins listening to the CAN-BUS through the CAN shield [5]. Communication between the Arduino and CAN shield is via SPI.

6. Once the message containing the State of Charge or another desired quantity is intercepted on the CAN bus, the message is decoded, and the desired value is retrieved. It is then passed back to the Zigbee end node [3] via Serial.

7. The Zigbee end node [3] constantly monitors the Serial bus. Once it receives the message from the Arduino, it passes that message as part of a packet to the Zigbee coordinator [2].

8. Upon receiving a packet , the Zigbee coordinator [2] passes its contents to the Billion gateway [1] via RS232.

The most important feature to note is that the state of charge is retrieved on request from the gateway. The in-vehicle meter does not send updates of its status at periodic intervals, as may have been predicted. This is due to a limitation of the Billion gateway. Therefore, the state of charge data is not pushed from the sensor side, but rather pulled from the charging station side. Very important consequences arise because of this. First, when a vehicle arrives at a charging station, it cannot announce its own presence because the charging station must first prompt it for a response. In order to do this, the station must first know that a new EV arrived from the smart-phone authentication procedure. Second, updates can only take place at the rate at which requests are issued and processed. Fortunately, the state of charge is a quasi-static value and a rapid refresh rate is unnecessary.

The configuration has been tested and results have demonstrated that the communication between the charge station and the SOC meter have been intermittent. It was possible that software upgrades were made to the charge station's Billion gateway without taking the SOC into account.

There has been challenges in collection SOC data. This information can only be collected when the EV driver activates the charger and the EV is equipped with a SOC box (only available to Nissan Leaf and to selected users.). Additionally, the EV will turn its CAN bus circuits off while it is in idle status. In this project, we only attempt to collect data while the EV is being driven.

In this project, we are asking EV users to enter "remaining mileage" as a base to estimate the beginning SOC and the ending SOC are estimated by the amount of energy received by the vehicle.

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4. Various EV charging - EV Make and Model

4.1. Data Collection

According to Task Order EV-UCLA-PS03-A, to date, UCLA EV Team has purchased/leased the following vehicles:

1. Nissan Leaf
2. Chevy Volt
3. Ford Focus
4. Tesla Model S - leased
5. 1st Mitsubishi MiEV – decommissioned from UCLA, waiting to be delivered to LADWP pending on agreement modification.
6. 2nd Mitsubishi MiEV – waiting for license plate to arrive.

4.2. Energy Efficiency on Grant Vehicles

Estimated Vehicle efficiency based on monthly observation (readings from dashboard, driving experiences) on grant vehicle:

Grant Vehicles	Energy Efficiency (miles/kWh)	Battery size	Average Range when fully charged	Battery degradation and other battery related observations
Tesla Model S	3.81	60 kWh	208	No obvious degradation observed.
Nissan Leaf	4.30	24 kWh	72	Obvious degradation observed, battery depth reduced by about 3-5 % after 2 years of testing
Chevy Volt	3.49	16 kWh	40	The battery condition is still very good.
Ford Focus	3.21	23 kWh	70	Minor degradation observed
Mitsubishi i-MiEV	3.97	16 kWh	61	Used for V2G experiment. Not enough data to make observation.

Overall Nissan Leaf has the highest Energy Efficiency overall. However, it all depends on EV driver's driving pattern. Chevy Volt's battery is quite well protected, it charges only at 3.3 kW level. There are no obvious degradation of battery observed.

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4.3. Observation of EV make and Models

4.3.1. Chevy Volt, Ford Focus, MiEV and Nisan Leaf Charging

Some of the specific observations we have found include impacts on voltage drop on the ability to send power to the vehicle and we have found that in certain vehicles such as the Chevy Volt the sensitivity to voltage fluctuations on the ability to get a charge is high; the inability to re-start a stopped charging session after the charging cable is disconnected on the Ford Focus; and this is contrast with the flexibility of input characteristics such as the above on the consistency of the charging behavior of Nissan Leaf. UCLA EV team has been continuously conducting experiments such as the above, and continues to do so, and will include these results in the final deliverable reports. Such variations in behavior are also resulting in us modifying the nature of the architecture of our system so as to make the overall architecture more robust and reliability in the presence of multiple EVs. Additionally, where feasible, we have reached out to the various EV manufacturers about some of our findings and are pursuing various lines of discussion on potential solutions by way of technological solutions and/or standards modifications so as to standardize the communications between the EVs, the charging stations and eventually the smart grid.

Drivers with different vehicle makes, different commute distances, different work habits such as where they charge (at home, in the office, in public places, etc.) and different work hours have different requirement for charging preferences. To be able to accommodate such a multitude of influencing factors on the smart charging scheduling, the purchased and leased vehicles are assigned to researchers and staffs in UCLA EV project team with various EV charging needs/preferences to test the scheduling algorithms. The driver also utilizes the mobile application developed in this research to specify his/her charging preference based on the make and model of the vehicle that was assigned to him/her. Eventually, the decision of where to charge, when to charge, how much to charge and which algorithms to be used to charge an EV would depend on a combination of personal driver preferences, facilities available for charging in parking facilities (such as at work, at home and at public places) and the programs offered by the grid operators including TOU pricing, renewable energy availability, etc. These and related topics are being researched.

Due to the significant variations in features among the different vehicles, in addition to the above usage for charging an EV, Mitsubishi MiEV is also used for V2G development and research, Nissan Leaf is used to level 3 CHAdeMO interface and backfill research, Chevy Volt is used as a influencing factor for being a hybrid vehicle (perhaps this may result in a less urgent charging need than pure electric and it could have an impact on scheduling algorithms especially when prioritizing who should get the energy first during limited time availability of energy such as perhaps during a Demand Response event), and Tesla Model S is being used currently for design and test of higher charging power experiments. In addition, Nissan Leaf and Chevy Volt were also both used to develop SOC modules to transmit battery status of charge (SOC) and BMS fault signals to the EV chargers and then back to the control center as an input to smart scheduling. These are a subset of the examples of the specific research experiments ongoing currently and to be performed and will be addressed in details in the final report.

The following sections are summaries of issues related with EV make and model UCLA has encountered. The problem with Tesla Model S will be discussed in a separate section in this report.

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4.3.1.1. Nissan Leaf

Nissan Leaf is used for smart charging (Level I, II and III) demonstration. The charger design has taken into consideration the flexibility of charging behavior of Nissan Leaf. Due to it is compatible with CHAdeMO protocol, it is also used for research in Level III. It is also used for research in battery State-of-Charge (SoC) monitoring. SOC modules has been designed for Nissan Leaf to transmit battery SOC and BMS fault signals to the EV chargers and then back to the control center as an input for smart scheduling. Preliminary observation and tests were conducted to study Nissan Leaf's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support and limited time, it is not feasible to perform V2G demonstration on these vehicles at this time.

4.3.1.2. Chevy Volt

Chevy Volt is primarily used in smart charging (Level I and II) demonstration. Charger design has taken into consideration the impacts of unable to charge due to voltage drop (below 190 VAC) on Chevy Volt. On algorithm design end, Chevy Volt is considered as an influencing factor for being a hybrid vehicle (less urgent charging need than pure electric). SOC modules has been designed for Chevy Volt to transmit battery SOC and BMS fault signals to the EV chargers and then back to the control center as an input for smart scheduling. However, at a recent vehicle software update, the SOC information was further encrypted and we are unable to retrieve this information right now.

Another observation of Chevy Volt is its alarm system that will be activated when the EVSE lost it power. This problem can be resolve by changing the setting inside the vehicle.

Due to the fact that it has only AC onboard single-direction charger, it is not used for V2G demonstration. Preliminary observation and tests were conducted to study Chevy Volt's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support and limited time, it is not feasible to perform V2G demonstration on these vehicles at this time.

4.3.1.3. Ford Focus

Ford Focus is primarily used in smart charging (Level I and II) demonstration. Charger design has taken into consideration the fact that it is unable to re-start charging session after charging disconnection of Ford Focus. Another observation is that Ford Focus will not be able to enable charging if the charging session power is not provided within 5 minutes after it is plugged in.

Due to the fact that it has only AC onboard single-direction charger, it is not used for V2G demonstration. Preliminary observation and tests were conducted to study Ford Focus's battery connection for possible V2G operation. However, due to safety, warranty, lack of vendor support and limited time, it is not feasible to perform V2G demonstration on these vehicles at this time.

4.3.1.4. Mitsubishii-MiEV

Mitsubishi MiEV is primarily used for demonstration of power back-feeding, smart charging (Level I, II and III) and design of renewable integration. The Mitsubishi MiEV is equipped with both J1172 and CHAdeMO, making it compatible with three levels of charging. The V2G function developed is based on the V2X box.

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Currently, the V2X box was used to withdraw the AC 100 V power from the vehicle and then the AC power was converted into 48 V DC and then connected through a grid-tie inverter to conduct V2G project.

4.3.1.5. Fiat 500e

The Fiat 500e model can only charge using the full power source. In addition, the EV user must submit a charging request to make the pilot signal draw a high current before plugging-in the cable. The initialization charging process fails if the duty cycle of the pilot signal is small, which indicates only low charging current is available. If the initial duty cycle is high and later changes to a lower one, the Fiat EV will generate the error messages of "Service Vehicle Electrical System" and "Service Your Charging Station".

4.3.2. Data collection on level 1 - Balancing utilization

On days when the number of public EVs is low, our own EV drivers try to plug into the level 1 so that we have sufficient data that is meaningful on a statistical basis for level 1 chargers, as the public typically plugs into level 2 if they are available.

4.3.3. SOC calculations

Given that J1772 is currently not providing SOC, and given that the SOC plugin does not work uniformly for ALL EVs, we enter the SOC information manually in the App. Given that there is no way to verify if the public users are entering the information correctly, our own team driving our own EVs diligently enters the correct information so that our data is accurate. Eventually, this difference will be used as a basis for data analysis.

4.3.4. Switchover time

The switchover time for between start and stop of multiple EVs plugged into a charger might vary with the type of EV. We have observed unusual behavior and so our own EV drivers need to test by manually removing and inserting the J1772 plugs. This is not feasible to do with other EV owners as it may wear out their J1772 plus. For that reason, our own research team needs all the models.

4.4. Tesla Integration Issues

4.4.1. Summary

	Issue	EVSE #	Date Detected	Symptom
1	Charging Cable Fault	PS8 201	Oct 20, 2014	No power into battery through cable
2	Failure to start charging after deactivation on a Level II EVSE	PS2 202	Aug 8, 2014	Algorithm cannot restart charging on Level II EVSE after modifying duty-cycles

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3	Failure to switch charging sessions on a Level I EVSE	PS9 401	Sept – Nov 2014	Algorithm cannot activate charging for Tesla after multiple sequences of activation and deactivation
4	Failure to charge on Level II EVSE with multiple connected EVs	All Level II EVSEs	Oct 2014	Tesla fails to start charging session when there are already EVs charging on the same EVSE
5	Sporadic failure to charge on Level II EVSE	All Level II EVSEs	Oct 2014	Tesla sometimes fails to start charging session even if no other EVs are present
6	Fail to consume energy on Level II EVSE	PS4 all plugs	June 2014	Tesla can start charging session but cannot get any power
7	Demand Response (DR) Capability	All UCLA Chargers	November 2015	Tesla only supports limited demand response functions.
8	DC V2G Capability	V2G Charger	November 2014	Tesla does not support DC V2G
9	CHAdeMO V2G Compatibility	V2G Charger	November 2014	Tesla charger is not compatible with EVSEs using CHAdeMO protocol

4.4.2. Charging Cable Fault

We are unable to initiate charging on Level 1 EVSEs that use the price-bid algorithm. The failure occurs as follows. When a Tesla user submits a charging session to the control center, the meter/relay of the EVSE initially turns on, but the algorithm, running on the server, automatically closes the session. If we attempt to reactivate the charging session using the mobile app, the EVSE's charging light turns on, but the power cable does not function properly – the light on the power source adapter becomes red, the charging port starts blinking red, and the dashboard reads "Charging Cable Fault." With regard to the dashboard's message, the Tesla's user manual states that a proper charge setting requires the charging port to have a stable green light and the adapters to display flowing green arrows.

To verify the charging cable failure, we conducted experiments using a second charging cable from Tesla. We found that the second cable functions properly. Therefore, the solution for this issue is to replace the charging cable. While this may be the case for this situation, it is not clear currently what the reason for such variability is. Causes could be related to the variation in the software within the vehicle being

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upgraded but working for a newer model of the charger while not working for an older model, or a myriad of other possibilities which will be explored in the remainder of this project.

4.4.3. Unable to start charging on Level II EVSE

This issue occurred on Outlet 1 of the Level II EVSE in Parking Structure 4. The Level II EVSE was running the price-bid algorithm that dynamically allocates duty cycles to each plugged in EV. Generally, if the duty cycle, assigned through user preferences, is lower than 10%, the algorithm disables the charging session until the other EVs finish charging or leave. During our observation, when the EV connected to the 4th outlet finished charging, the server-side algorithm correctly enabled the charging session for the Tesla connected to Outlet 1 and set the duty cycle to 13%. However, the charging current remained lower than 10% during the initial 6 to 10 seconds; at which point, the algorithm assumed the Tesla had fully charged and closed the charging session as show in Figure 133. This delay in the charging current seems to affect the Tesla, because we have observed the charging current rise in about 3 seconds for other EVs, such as the Nissan Leaf and Chevy Volt.



Figure 133 Algorithm closes the Tesla's charging session

We devised a temporary solution for the Tesla by prolonging the delay time in the price-bid algorithm to allow time for the current to increase. We also conducted experiments and discovered that the Tesla has a complex internal battery management system (BMS), which adaptively controls charging behaviors based on the power source; thus, the time required to initiate charging will be different at varying times. However, it is not fully clear as to whether this approach is generalizable and also we need to conduct experiments comparing with different EVs. This can be a potential challenge to EV charging.

4.4.4. Failure to Switch Charging on a Level I EVSE (Price Bid Algorithm)

This issue occurs on the Level 1 EVSE that uses the price-bid algorithm. This algorithm allocates energy (charging time) to EV users based on their price preferences and switches charging sessions among users who are connected to the same EVSE. In the case of the Tesla, we have observed that after switching several times, the vehicle will not resume charging. We have not encountered this issue with other EVs, such as the Nissan Leaf or Chevy Volt.

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To investigate this problem, we examined the Tesla's historical charging records when charging on a Level EVSE with the price-bid algorithm. We found the same problem occur in the charging sessions in Figure 134, Figure 135, and Figure 136. In each case, we observe that the Tesla successfully reactivates charging four times and fails on the fifth attempt. We are trying to determine why this is occurring and this requires further research and a large number of test cases and data collection.

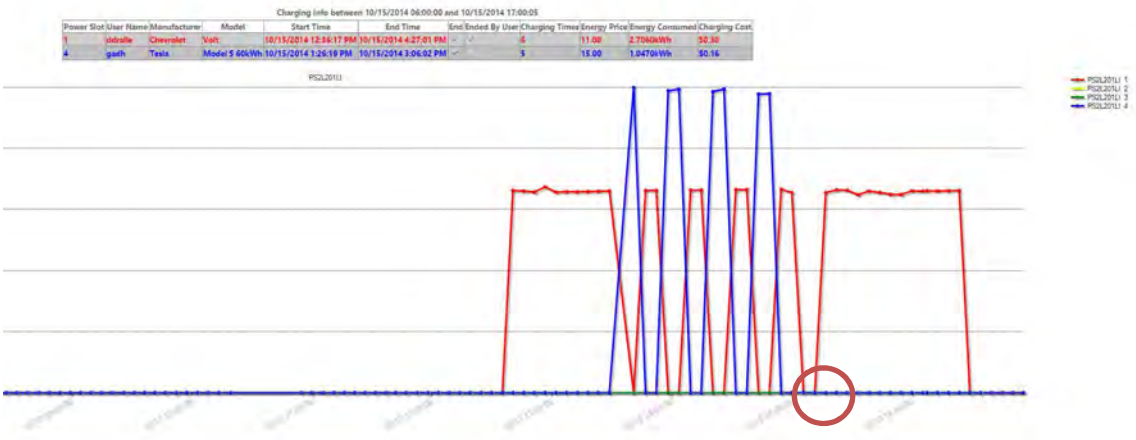


Figure 134. Charging session on 10/15/2014

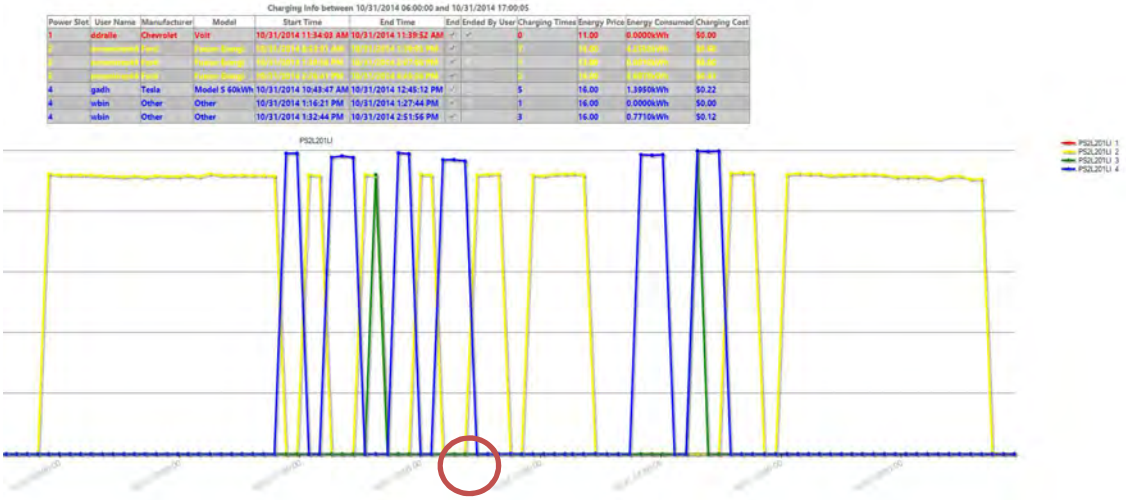


Figure 135 Charging Session on 10/31/2014

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Figure 136 Charging Session on 11/3/2014

We verified the scenarios in these charging sessions through an experiment in which we virtually activated and deactivated the EVSE's meter/relay every five minutes, simulating the switching behavior of the price-bid algorithm. The following table shows the experimental data.

Experiment simulating the switching behavior of the price-bid algorithm on a Tesla

Timestamp	Meter/Relay Status	Dashboard Message
13:50	On	charging
13:54	Off	charge interrupted: check power source
13:59	On	starting to charge, 2 sec, charging
14:04	Off	NO WALL POWER: power interrupted,check power source
14:09	On	starting to charge, 2 sec charging
14:14	Off	NO WALL POWER: power interrupted,check power source
14:19	On	starting to charge, 2 sec, charging
14:24	Off	charge interrupted: check power source
14:29	On	startting to charge, 5 secs, charge stopped.
14:32	Off	ready to charge
14:35	On	startting to charge, 10 secs, charge stopped. **(Fail to Charge)**

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14:36	Off	ready to charge
14:38	On	starting to charge, 10 secs, charge stopped. **(Fail to Charge)**

As a temporary solution for this issue, we increased the time quantum from 30 minutes to 60. However, we must consider the tradeoff between the switch times and length of each time quantum. For example, if we decrease the length of each time quantum to 30 minutes, Tesla users will likely reach the maximum limit of five switch times. On the other hand, if we make the time quantum too long, we risk harming the equitable consumption of energy among other users; they will have to wait very long to get energy, which will affect their travel schedules. The length of time interval needs to be investigated and will be varied along with a few other variables for further research. This also requires a substantial amount of data collection and analysis.

4.4.5. Failure to charge on a Level II EVSE with multiple connected EVs

We have observed the Tesla failing to start a charging session when other EVs are already charging at the same EVSE. We believe that the Tesla does not accept our start charging process when the EVSE is already running, because the EVs connected to outlets 2-4 go through a redistribution of the duty cycle at the end of the start charging process. To solve this issue, we have moved the redistribution of the duty cycle for charging multiple EVs to the beginning of the start charging process. It is important to solve this problem as our approach is designed to be grid friendly – i.e. the charging rates are controllable and flexible and in the absence of such capability, the Tesla charging may not be scalable when it comes to grid-friendliness. This problem is being researched further.

4.4.6. Inconsistent Charging on Level II EVSE

We have observed that the Tesla sometimes fails to initiate a charging session regardless of other EVs charging on the same EVSE. We attribute this case to the Tesla having a higher standard requirement for the pilot signal voltage as compared to other EV brands. To resolve this issue, we replaced the output resistors and amplifiers of the pilot signals to meet the SAE J1772 standard.

4.4.7. Failure to Consume Power on a Level II EVSE

We have observed that the Tesla sometimes fails to consume power on a Level 2 EVSE in Parking Structure 4. We have identified two potential reasons for this problem. First, it could be a characteristic of our EVSE which allows dynamic current modification even though we have implemented as per the SAE standard. In comparison, the other EVs work appropriately which implies that differences in the implementation with the Tesla charging technology is probably the cause – this needs to be investigated further. Second, some of the plugs in the Level 2 EVSE may have connection issues which in the context of the Tesla get exacerbated further as the Tesla outlet requires an adaptor to connect to the SAE J 1772 connector on the vehicle; in this case, we will have to experiment further with replacement/refinement.

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4.4.8. Demand Response Capability Limitation

Due to above issues, Tesla has limited support for Demand Response (DR) signals, which are broadcast by utility control center may request engaged vehicles to curtail the power consumption or stop charging for a pre-defined time range. Once DR signals finished, power consumption should be restored to original levels which involves commands to start charging, stop charging and modify duty-cycle for a charging session. The foreseeable mal-functions are: 1) incorrect value of power consumption; 2) not responsive to DR signals after a limited times. The issue of restoring original power consumption level is resolved by updating Tesla's software.

4.4.9. DC V2G Capability

Tesla does not have a DC port that supports V2G bidirectional charging, which is an important aspect that EVs can support future power grid. It results from the fact that there is no DC port wired directly from the batteries, and the fact that there is no bi-directional on board inverter.

4.4.10. CHAdeMO V2G Compatibility

Currently, CHAdeMO is still the most popular solution for V2G. A lot of V2G inverters are manufactured under CHAdeMO protocol. However, Tesla does not use CHAdeMO protocol, making it inaccessible to most existing V2G facilities. Customized hardware and compatible software need to be designed in order to activate the V2G function.

5. Research Issues on Electric Vehicles

5.1.1. Charging Parameter Identification and Control Strategy

To integrate Tesla into a charging system that uses complex algorithms, we will need to conduct further experiments to measure the vehicle's charging parameter, so we can refine our control algorithms. The parameters to study include the following:

Current Ramp up Time (Level I & II) indicates the minimum time needed for the Tesla to initiate charging and increase the charging current to an acceptable value, currently set to 0.5A and needs further research and refinement to draw any conclusions.

Maximum number of consecutive on/off actions indicate the maximum number of times a Tesla can switch charging sessions on a Level I EVSE. In addition, we need to better understand the internal BMS mechanism, including the time interval between charging sessions. This time interval is crucial for the Tesla to assess the power source stability and properly initiate charging and requires further investigation.

Power vs Duty-cycle Diagram (Level II): A Tesla can consume as much as 6 kW with a duty cycle set to 50%, while a Chevy Volt consumes only 3 kW. This higher power consumption has potential to create an instant load peak for local distribution systems and lower the charging voltage for other EVs. We must further investigate the relation between the duty-cycle and power consumption within the Tesla's battery system in order to optimize our grid-friendly algorithms. A better understanding will also allow us to control the Tesla's power consumption by accurately setting the appropriate levels of the duty-cycle.

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shows a comparison of the power consumption between a Tesla and a Chevy Volt and this research needs further investigation.

Figure 137

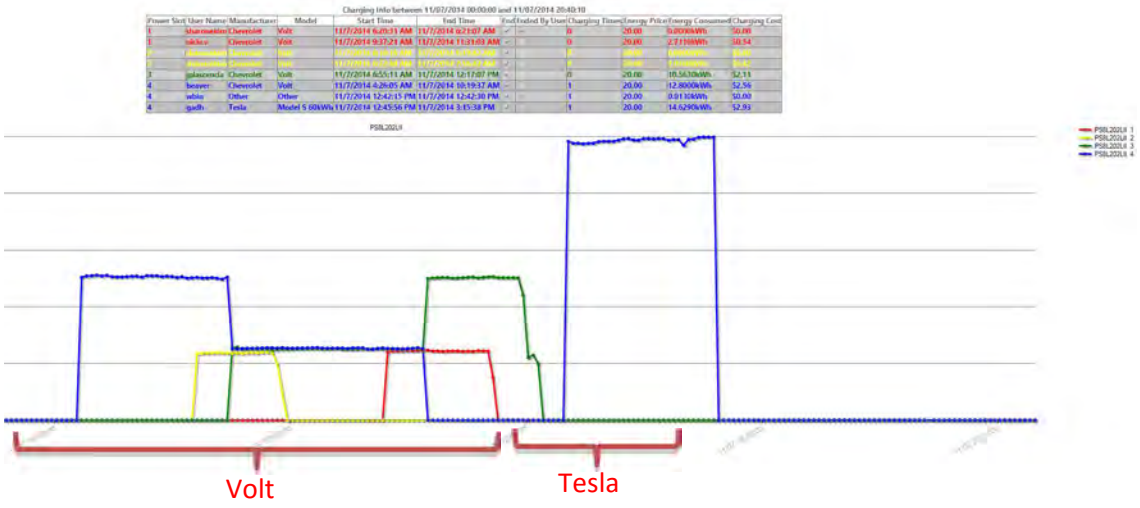


Figure 137 Comparison of power consumption between Tesla and Chevy Volt

5.1.2. Pricing and Scheduling Algorithms

We must further research and design the pricing and incentive strategy design with effective server-side algorithms to take advantage of the Tesla's larger battery. Its battery has a higher power consumption capability (60 kWh / 85 kWh) than other EV types, which can potentially make it a more effective mobile energy storage device for providing regulation and aggregation services. This is being investigated currently.

The service role of energy aggregator entails optimizing the local power grid by encouraging EV users to participate, using monetary regulation signals and other incentives. However, the regulation price signal is proportional to the available capacity to provide the regulation service. The Tesla has a probability of having a higher capacity remaining for the State of Charge (SoC), which makes it possible to change power consumption on a wider range and results in added complexity for the optimization problem within our algorithms. To compensate, we must add to the existing aggregator model the following components: the parameters that indicate monetary regulation services, EV users' preferences, and responsive coefficient (elastic matrix) – these are all topics for research in the next two years.

5.1.3. Start Debugging Issues Affecting other EVs

Since the start of the EV project, we have detected and typically resolved problem classes affecting individual EV models. For instance, the Toyota Prius had a particular type of problem when connected to a Level 1 EVSE in Parking Structure 9. We investigated this problem and other similar ones identified, and discovered that they were caused by the EV's setting, such as the timer not being closed, while others were caused by the EV's Level 1 adapter. We have been documenting such cases as they have arisen. We are now planning to actively survey our system's EV users to identify issues affecting EV classes including

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the Tesla, so we can analyze issues and solve them. Finding and debugging classes of problems that affect the Tesla constitute the next step in this research.

6. Wireless Communication Scalability Testing

6.1. The Structure of Existing Network and Problems

Intelligent EV charging infrastructures will play a key role in the evolution of the next generation transportation systems. Much of the current research and industrial initiatives already focus on various areas related to EVSE systems. As a result, network and communication scalability may become a critical issue for the ECSE network. For this reason, UCLA SMERC has studied and implemented networked charging stations, which are able to send and receive data, while a web-based application monitors their operation.

The deployment of the EV charging station network is described in detail in Section 2 of this report. In general, each parking structure level has several gateways that communicate with meters and sensors through the ZigBee protocol. Communication among the gateways can also adapt to the parking structure's particular needs by using other protocols such as PLC (Power Line Communication), Wi-Fi, 3G or even wire. Figure 138 shows how the gateways, meters, temperature sensors and control center are connected to each other in the communication network.

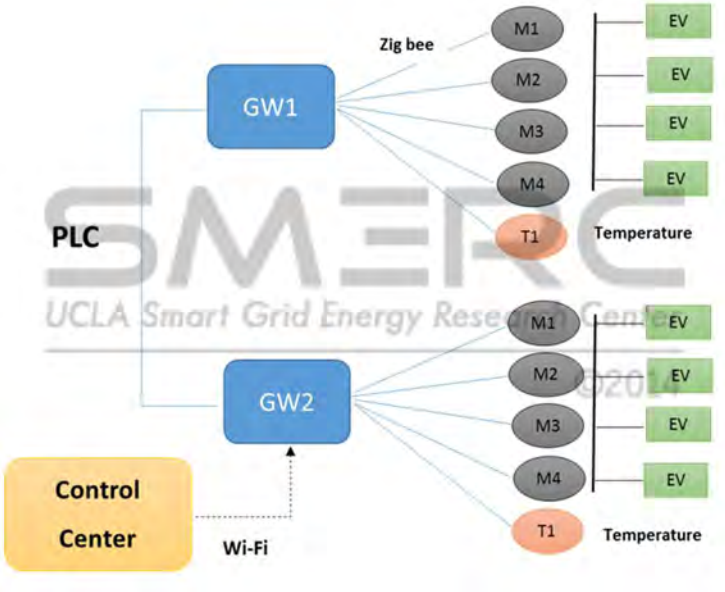


Figure 138. Parking Structure 9 wireless communication configuration

As seen in the figure above, each gateway includes four meters and one temperature sensor. The meters collect various power data (e.g., voltage, current, power factors, energy, and temperature) from the charging stations and send them periodically to the control center. Additionally, the meters also send control commands to the EVSEs to modify their operation based on the scheduling algorithm.

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6.1.1. Communication methods (Push/Pull)

The majority of the communication problems we have experienced with the existing network arise from the stability of the 3G and Wi-Fi connections to the control center. At times, these WAN connections are not stable and need to be re-initialized to connect to the Internet. The problem has been solved by switching the communication method between the Billion gateway and server from “Pull” to “Push”.

“Pull” is a transmission method initiated by the server. Upon receiving the request, the local gateway returns the latest power data of the requested entity. This process is highly dependent on the Internet’s stability. Due to this 3G/Wi-Fi connectivity setup, an occasional connection failure results in loss of data for the corresponding request.

On the other hand, “Push” is a transmission method initiated by the client (the gateway in this case). In this configuration, the gateway sends its data at a preset time to the server. If the connection fails, the local gateway keeps the data and retries the transfer in the next cycle. Push requests reduce the network traffic from two times per request (forward and backward) to only one time per request (incoming data). The current data collection process uses the Push method for solar panels (3G) and temperature sensors (Wi-Fi, Ethernet, 3G), while a Billion gateway ensures that the server receives all the data. This arrangement has resulted in the acquisition of a complete data set over several months.

However, not all problems have been resolved from the switch in communication methods. An additional problem arose when the power meters started disconnecting from the gateway. This problem was overcome by customizing the communication protocols between the gateway and meters with the Keep connection function that enabled the network to reclaim the dropped meters.

6.2. Virtual Devices

To facilitate research and experiments on the wireless infrastructure, SMERC is using its newly constructed Super Control Center (SCC) servers to simulate Virtual Devices (VDs). A VD is a virtual EV charger that can simulate Level-1 (low power) and Level-2 (high power) functions with a randomly distributed charging profile. A VD also supports the same Demand Response protocols operated in the EV Control Center. By integrating the VD program in distributed servers interconnected with wireless communications, we can test the scalability of the current EV control network without expanding the actual number of charging stations.

6.3. Network communication modeler

Another method of studying the existing network’s scalability uses the Riverbed modeler [29]. This discrete event-simulation engine comprises a suite of protocols and technologies within a development environment to analyze and design communication networks. By modeling all network types and technologies (e.g., VoIP, TCP, OSPFv3, MPLS, and IPv6), Riverbed Modeler analyzes networks to compare the impact of different technology designs on end-to-end behavior. Figure 139 depicts some of the functions in Riverbed Modeler, which provides high-fidelity modeling, scalable simulation, and detailed analysis of a broad range of wired and wireless networks.

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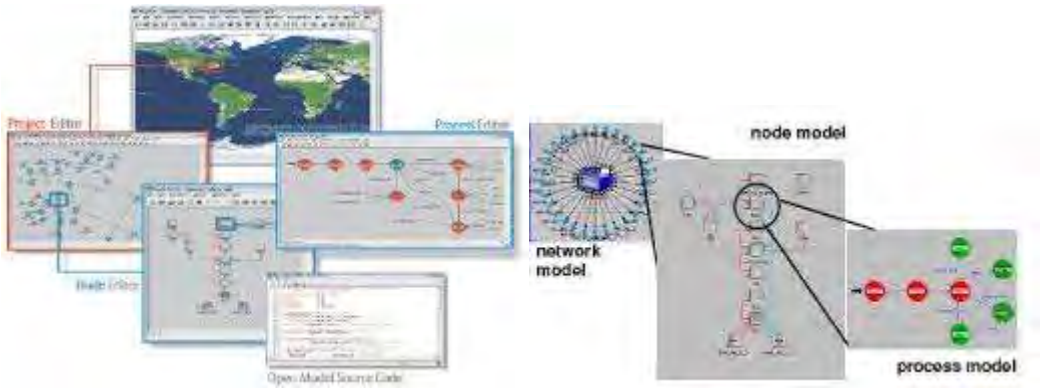


Figure 139. Riverbed Modeler [29]

In the past 6 months, UCLA created a few network models to simulate the existing network based on the configuration of existing parking structure. Due to lack of vendor support and limitation on the simulators, we were unable to obtain conclusive result from Riverbed simulations. As an alternative approach the Virtual EV chargers (Devices) in Super Control Center will be used to emulate large scale communication network challenges.

7. Conclusion

UCLA Smart Grid Energy Research Center (SMERC) take pride in the achievement accomplished in this project. The following is a list of key achievements:

- Deployed **191** smart EV charging points with **269** EV participants and a total of **25** GB of data for research and analysis under this project.
- Implemented smart EV charging stations with current throttling and multiplexing capability.
- Implemented WinSmartEV^{TM} platform for integration and scheduling algorithms.
- Implemented V2G system with Mitsubishi MiEV Power box for back-feed operation.
- Integrated BESS, PV and DCFC for load balancing and power management.
- Published **28** journal/ conference papers, **2** accepted patents and **4** pending patents.

UCLA SMERC continues to make progress on this project with active project demonstration, data collection, data analysis and publication of research results based on the data obtained. Research is ongoing in the development of optimizing EV charging scheduling depending upon various inputs such as user preference, grid status, solar panel output, integration of BESS systems and demand response events. The UCLA EV team continues to study & compare a variety of EV network technologies, perform appropriate & related research, as well as continue to perform the demonstrations in this project.

The following is a list of prominent benefits to power and EV industry as a result from this demonstration project.

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- The unique current throttling feature of the charger created in this project allows for flexible power management schema to increase power quality and grid stability.
- The multiplexing features along with scheduling algorithms maximized and optimized usage of existing power circuits
- The implemented WINSmartEV^{TM} platform allows rapid integration of various components such as V2G, BESs, PV and DCFC for power management.
- The lessons learned and best practice identified in each Use Case along with the amount of data collected and EV user participation provide valuable reference for future large scale EV charger deployment.

8. Publications

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2. Wang, B. Hu, C. Qiu, P. Chu and R. Gadh, "EV Charging Algorithm Implementation with User Price Preference", IEEE Innovative Smart Grid Technologies, 2015, accepted
3. Chynoweth, Joshua; Chung, C.; Qiu, C. et al, “Smart Electric Vehicle Charging Infrastructure Overview “, 2014 IEEE PES Conference on Innovative Smart Grid Technologies (Pending)
4. Chung, J. Chynoweth, C. Qiu, C. Chu, R. Gadh, "Design of Fair Charging Algorithm for Smart Electrical Vehicle Charging Infrastructure", International Conference on ICT Convergence 2013, Jeju, Korea, Oct. 14-16, 2013
5. Chung, J. Chynoweth, C. Qiu, C. Chu, R. Gadh, "Design of Fast Response Smart Electric Vehicle Charging Infrastructure", IEEE Green Energy and Systems Conference, IGESC 2013, Long Beach, U.S.A., Nov. 25, 2013
6. C. Chung, E. Youn, J. Chynoweth, C. Qiu, C. Chu, R. Gadh, "Safety Design for Smart Electric Vehicle Charging with Current and Multiplexing Control", 2013 IEEE International Conference on Smart Grid Communications, Vancouver, Canada, 21-24 October, 2013
7. C. Chung, A. Shepelev, C. Qiu, C. Chu, R. Gadh, "Design of RFID Mesh Network for Electric Vehicle Smart Charging Infrastructure", 2013 IEEE International Conference on RFID Technologies and Applications, IEEE RFID TA 2013, Johor Bahru, Malaysia, 4-5 September, 2013
8. C. Chung, P. Chu, R. Gadh, "Design of Smart Charging Infrastructure Hardware And Firmware Design of The Various Current Multiplexing Charging System", Seventh Global Conference on Power Control and Optimization PCO 2013, Prague, August 25-27, 2013.
9. H. Nazaripouya , Y. Wang, P. Chu, H. R. Pota , and R. Gadh, “Optimal Sizing and Placement of Battery Energy Storage in Distribution System Based on Solar Size for Voltage Regulation” 2015 IEEE PES General Meeting (Pending)
10. M. Majidpour, C. Qiu, P. Chu, R. Gadh, H. R. Pota, “Fast Prediction for Sparse Time Series: Demand Forecast of EV Charging Stations for Cell Phone Applications”, to appear in IEEE Transaction on Industrial Informatics.

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9. Patents Filed

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1. R. Gadh, S. Mal, S. Prabhu, C. Chu, J. Panchal, O. Sheikh, C. Chung, L. He, B. Xiao, Y. Shi, “Smart Electric Vehicle (EV) charging and grid integration apparatus and methods” – US 2013/0179061 a1 – UC-2010-903-2-LA, , Publication number US9026347 B2
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