Automated Dynamic Demand Response Implementation on a Micro-grid

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ABSTRACT

In this paper, we describe a system for real-time automated Dynamic and Sustainable Demand Response with sparse data consumption prediction implemented on the University of Southern California campus microgrid. Supply side approaches to resolving energy supply-load imbalance do not work at high levels of renewable energy penetration. Dynamic Demand Response (D^2R) is a widely used demand-side technique to dynamically adjust electricity consumption during peak load periods. Our D^2R system consists of accurate machine learning based energy consumption forecasting models that work with sparse data coupled with fast and sustainable load curtailment optimization algorithms that provide the ability to dynamically adapt to changing supply-load imbalances in near real-time. Our Sustainable DR (SDR) algorithms attempt to distribute customer curtailment evenly across sub-intervals during a DR event and avoid expensive demand peaks during a few sub-intervals. It also ensures that each customer is penalized fairly in order to achieve the targeted curtailment. We develop near linear-time constant-factor approximation algorithms along with Polynomial Time Approximation Schemes (PTAS) for SDR curtailment that minimizes the curtailment error defined as the difference between the target and achieved curtailment values. Our SDR curtailment problem is formulated as an Integer Linear Program that optimally matches customers to curtailment strategies during a DR event while also explicitly accounting for customer strategy switching overhead as a constraint. We demonstrate the results of our D^2R system using real data from experiments performed on the USC smartgrid and show that 1) our prediction algorithms can very accurately predict energy consumption even with noisy or missing data and 2) our curtailment algorithms deliver DR with extremely low curtailment errors in the 0.01-0.05 kWh range.

Keywords

Dynamic Demand Response, Automated Demand Response Implementation, Consumption Prediction, Reduced Consumption Prediction, Customer Selection

1. INTRODUCTION

Technological advances such as bi-directional smart meters allow remote monitoring and control, thus transforming the traditional power grids into complex cyber-physical systems [10]. 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.

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 incentivising 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 $\mathrm{D^2R}$ where the utility needs to schedule and implement a DR in few hours of notice due to dynamically changing grid conditions [3].

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. In [5, 3] and [11], we discuss challenges, evaluation metrics and prediction models such as time series models, regression tree based models for accurate prediction of individual building energy consumption. The various models are discussed briefly in this paper.

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. We developed several algorithms for optimal customer selection which are discussed in detail in [26, 15] and [14]. In this paper, we provide a brief description of such algorithms.

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.

In this paper, we discuss the architecture of the Demand Response program implementation. For completeness, we briefly discuss the prediction and optimization models. These models have been discussed in detail in the papers referenced in the respective sections. We qualitatively evaluate one of the DR event performed in campus and show that an energy curtailment of 2100 kWh was achieved in the DR event of 4 hours.

In Section 2, we discuss works done in the community related to energy consumption and reduced-consumption prediction and customer selection. The implementation details are discussed in Section 3. In Section 3.1, we give an overview of the various components involved in the DR implementation on our campus microgrid. The prediction models used are discussed in Section 3.2. The algorithms used for optimal building strategy pair selection are discussed in Section 3.3. We evaluate the various components involved in our implementation and the entire system in Section 4 and provide concluding remarks in Section 5.

[1]In this paper we use the terms building and customer interchangeably

2. RELATED WORKS

Existing consumption prediction approaches include our and other works on time series models, regression trees, artificial neural networks and expert systems. Utilities also use averaging models based on recent consumption due to their simplicity. In [25], authors evaluate time series methods for load forecasting by comparing them against other methods. In [13], authors investigate seasonal time series forecasting models. We developed regression tree models using weather and schedule data in [4] and evaluated the effect of feature combinations on the prediction accuracy.

While electricity consumption prediction has been studied widely, there has been less focus on the prediction of curtailment during a DR event. The problem of planning short-term load curtailment in smart grid is discussed in [17, 22]. Our prior work [7] addresses the challenges in curtailment prediction and provides an efficient algorithm for the same.

Traditionally, customer targeting for DR were performed based on aggregate customer consumption data obtained from monthly billing data or surveys [18, 19]. DR algorithms that perform such customer targeting include dynamic programming based peak load minimization [9], particle swarm optimization based DR algorithms [21] and game theoretic solutions constrained by real time pricing [8] and customer comfort levels [6]. However, as shown in [23], such approaches are highly inaccurate. The aggregate billing data does not necessarily reflect the consumption profile of the DR day and moreover, the selection in such works is done oblivious to the varying load profile through out the day. Hence, such work do no guarantee the smoothing of peaks in electricity consumption.

Works using fine grained data from smart meters include [24] where a quadratic programming formulation is developed for DR optimization. However, the assumption in the paper that continuous curtailment values can be obtained by customers runs counter to the discrete curtailment values obtained in the buildings in USC microgrid. A stochastic knapsack based algorithm for selecting the right customers to maximize the probability the desired curtailment value is achieved over the period of the entire DR event while limiting the utility's cost is developed in [16]. However, the algorithm relies on the central limit theorem, normal distribution of curtailment values and has the implicit assumption that there are a large number of customers are available to select a subset from.

3. IMPLEMENTATION OF DEMAND RESPONSE ON A CAMPUS MICROGRID

3.1 Overview

3.1.1 Dynamic Demand Response (D^{2}R)

We define Dynamic Demand Response (D^{2}R) as the decision making about *when*, *by how much* and *how* to reduce electricity use by the demand side in response to dynamically changing conditions of generation and consumption [3]. Traditionally, the timing and the duration of DR event is fixed in advance and the strategies are pre-determined. D^{2}R brings flexibility to the timing and duration of the DR event informed by fine-grained data and prediction models. Such a technique allows the utilities to implement a DR event in short notice when the expected demand becomes too high or expected generation capacity drops too low.

3.1.2 D^{2}R Implementation Overview

We have implemented D^{2}R on the University of Southern California (USC) microgrid. The USC microgrid consists of over 170 buildings equipped with around 50,000 smart meters which provide power consumption data in regular intervals of 15 minutes [2]. Buildings on our campus are equipped with advanced energy curtailment strategies which can be administered remotely by the USC Facilities Management Services (FMS). Strategies include techniques such as Global Zone Temperature Reset (GTR), Variable Frequency Drive Speed Reset (VFD), Equipment Duty Cycling (Duty) and their combinations. [20]

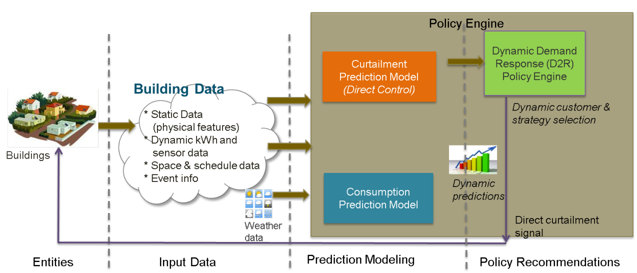

Figure 1: Control and Data Flow For Dynamic Demand Response Implementation

A simplified control and data flow diagram of our D^{2}R implementation is shown in Figure 1. The USC FMS initiates a DR event using OpenADR messages typically for 4 hours from 1 pm to 5 pm during weekdays. A targeted curtailment value is provided which needs to be achieved over the entire DR event. A set of available buildings is also provided by the FMS. 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. The power consumption data aggregated in 15 minute intervals by the smart meters is stored into a database to be readily available when required. State-of-the-art data driven models are used to predict *Baseline:* energy consumption by each building during the DR when none of the energy curtailment strategies are followed and the *Reduced Consumption:* energy consumption by each building following each available strategy during the DR. The predictions are performed for each 15 minute interval of the DR event. This information is then used by the optimization module to determine the set of building-strategy pairs for each 15 minute interval to achieve the targeted curtailment under various constraints which will be discussed later in this paper. FMS then communicates the selected strategy to each building using direct control to be implemented during the DR event.

3.2 Prediction Modeling

The Policy Engine (PE) includes a prediction engine which feeds into the optimization engine as shown in Figure 2. Two kinds of predictions are performed by the prediction engine: (1) Baseline consumption prediction and (2) Reduced consumption prediction. The prediction engine consists of a number of prediction models. One of these models can be picked for a single DR event for prediction. This allows us to perform experiments with different models to fine tune the accuracy of the predictions.

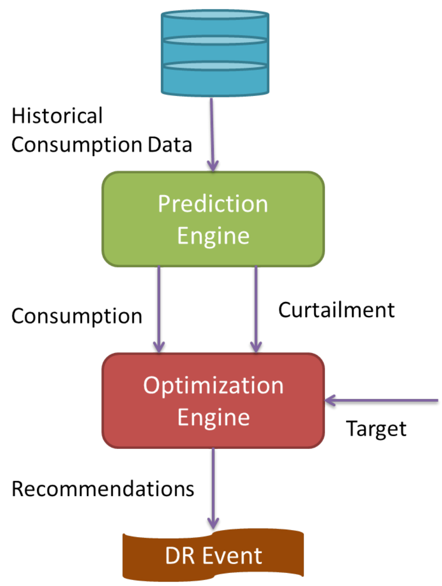

Figure 2: Policy Engine

The baseline consumption prediction models available in the prediction engine are discussed in the following subsections.

3.2.1 Averaging Consumption Prediction Models

The averaging models predict consumption by taking the average of the observed consumption in the previous days [3]. We implemented three averaging models in the prediction engine:

- **NYISO:** The New York ISO (NYISO) model's output is calculated from previous five days with the highest average kWh value. These days are chosen from a pool of ten previous days, which are selected starting two days prior to the event day, and excluding weekends, holidays, past DR event days or days on which there was a sharp drop in the energy consumption. In addition, a day is included in the pool only if the average consumption on that day is more than 25% of the last selected day. The process repeats until all ten days have been placed in the pool of days for baseline calculation. Days are then ranked based on average hourly consumption and five days with the highest value are selected. Finally, the baseline is calculated by taking hourly averages across these days.

- **CAISO:** According to the California ISO model (CAISO), the baseline is the hourly average of three days with the highest average consumption value among a pool of ten selected previous days. Selected days cannot be weekends, holidays, past DR event days. CAISOs performance can be considerably improved by introducing a morning adjustment factor. We denote this modified version of CAISO as CAISOm. In our experiments we consider both versions.

- **CASCE:** The Southern California Edison ISO model (CASCE) estimates baseline consumption by averaging over the past ten days. These days cannot include weekends, holidays or past DR event days. Once ten days have been selected, the baseline is calculated as their hourly average. Similar to NYISO, a morning adjustment factor is applied to the calculated baseline.

3.2.2 Regression Tree based Consumption Prediction

A Regression Tree (RT) model generates a decision tree with leaves of the tree ending in a regression function [3]. Regression trees are generated in a top-down fashion by choosing the most likely attribute for decision-making at each level. Each attribute that is chosen partitions the remaining training data into sub- sets depending on the value of the decision made. This method of recursive partitioning leads to smaller regions where simple models can be applied.

3.2.3 Time Series Consumption Prediction Models

The Auto Regressive Integrated Moving-Average model, known as ARIMA, is represented by ARIMA(p, d, q), where p is the number of autoregressive terms, d is the number of non-seasonal differences, and q is the number of lagged forecast errors in the prediction equation [3]. The parameter d is the order of differencing needed to make the series stationary. The parameters p and q are determined using autocorrelation and partial autocorrelation functions (using the Box-Jenkins test).

Readers can refer to [3] paper for a detailed analysis and comparison of the various baseline consumption models discussed briefly above.

3.2.4 Reduced Consumption Prediction

For predicting the reduced consumption during a DR event, the *DiCuf: Direct Curtailment Forecasting Model* [7] is used. It is a historical averaging model that uses previous values for the same time on similar DR days for the same <building, strategy> combination to forecast future reduced consumption. Specifically, predicted curtailed consumption is calculated by taking 15 minute averages across values from past "similar" DR events and placing them into bins of similar events. We consider past DR events per building to be similar if the same strategy was deployed.

3.3 Policy Recommendations

The optimization engine accepts the predicted consumption and reduced consumption from the prediction engine. It uses them to create a time varying curtailment matrix denoting the expected curtailment of the building strategy pairs available for the DR event. The curtailment matrix is used by the optimization algorithms to determine the set of buildings and the strategies they should adopt and provide this information as policy recommendation to the FMS for implementation.

Driven by our experience with DR implementation in USC, several customer (building) selection algorithms were developed. The model and assumptions used by the algorithms are discussed in Section 3.3.1. The various algorithms are discussed briefly in Sections 3.3.2- 3.3.6. Readers can refer to [26, 15] and [14] for detailed description of the algorithms discussed below.

3.3.1 Model and Assumptions

We are given a set of M customers (buildings) and N strategies. The entire DR period is divided into T discrete time intervals. Dynamic customer strategies are represented by a time varying curtailment matrix $\mathbf{C^t} \in \mathbf{R}^{M \times N}$ with element c_{ij}^t denoting the discrete curtailment value of customer i adopting strategy j at time interval t where $t \in \{1, \ldots, T\}$. Let $\mathbf{X^t}$ be the decision matrix with element x_{ij}^t denoting the corresponding decision variable at time t with γ denoting the achievable curtailment value across the entire DR event.

3.3.2 Heuristic for Customer Selection

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?* [26]. 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 bin range determined by coin c_i is $(c_i.v, c_{i+1}.v]$ where v is an appropriately chosen scaling factor. 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 γ.

3.3.3 ILP based Demand Response

While the heuristic described in the previous section provides a simple and fast technique to determine building-strategy pairs to achieve a targeted curtailment γ, the accuracy is unbounded. It can incur very high error rates for some inputs. Hence, we developed an Integer Linear Program for the problem of optimal customer selection [15]. The ILP determines the strategy each building should follow throughout the DR event. This is useful when only coarse grained data is available. If fine grained data is available, the ILP can be solved for each interval to determine the building-strategy pairs. Let $c_{ij} = \sum_{t=1}^{T} c_{ij}^t$ and x_{ij} denote the corresponding decision variable for the entire DR event. The ILP can be formulated as follows:

$$Minimize: \quad \mid \sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij}x_{ij} - \gamma \mid \tag{1}$$

$$Subject\ to: \sum_{j=1}^{N} x_{ij} = \ 1 \qquad \forall i\ \{1,\ldots,M\} \tag{2}$$

$$x_{ij} \in \{0,1\}, \qquad \forall i,j$$

Equation 2 ensures that a customer adopts exactly one strategy in the DR event. This includes the default strategy with a curtailment value of 0.

3.3.4 Sustainable Demand Response

The algorithm mentioned in the previous section might aggressively curtail the demand in some intervals while accumulating demands in other intervals. Such assignments have peaks in certain intervals, which can possibly exceed the generation capacity defeating the entire purpose of the DR event. To addresses this issue, we defined the notion of Sustainable Demand Response (SDR) [14]. SDR attempts to evenly smooth the curtailment over the entire period of the DR event.

We use the following ILP to model a Sustainable DR event.

$$Minimize: \sum_{t=1}^{T} \epsilon_t \tag{3}$$

$$Subject\ to: \mid \sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij}^{t}x_{ij}^{t} - \frac{\gamma}{T} \mid \leq \epsilon_t \qquad \forall t \tag{4}$$

$$\sum_{j=1}^{N} x_{ij}^{t} = 1 \qquad \forall i,t \tag{5}$$

$$\forall x_{ij}^{t} \in \{0,1\} \qquad \forall i,j,t$$

The objective is to minimize the $\|l\|_1$ norm (Equation 3).

3.3.5 Approximation Algorithms for Sustainable Demand Response

The ILP solutions mentioned above do not scale well with the number of buildings and strategies. The heuristic mentioned in Section 3.3.2 incurs unbounded errors which can be exceptionally high in certain cases. Hence, we develop approximation algorithms which scale well with the number of buildings-strategy pairs ensuring bounded error.

We developed a $\sqrt{2}$-factor approximation to achieve the optimal target during each curtailment period and therefore for the entire DR event. The algorithm sorts the customer-strategy pairs and picks the to achieve a curtailment value within the range $[\frac{\gamma}{T\sqrt{2}}, \frac{\sqrt{2}\gamma}{T}]$. The algorithm runs in $O(TM \log N)$ time when strategies are preprocessed in advance for a given curtailment target. The one-time preprocessing cost assuming apriori knowledge of curtailment strategies is $O(TMN \log N)$. While the fast $\sqrt{2}$-factor approximation algorithm briefly discussed above can be used to very quickly compute sustainable DR solutions, the error due to the $\sqrt{2}$-factor approximation may be unacceptably large in some cases. Therefore, using ideas from the subset sum problem [12] we developed a Polynomial Time Approximation Scheme (PTAS) that approximates the optimal solution provided by the ILP in Equation 3 to within an arbitrarily small ϵ-factor in time polynomial in MN/ϵ.

Readers can refer to [14] for further details on the algorithms.

3.3.6 Sustainable Demand Response with Strategy Overheads

Using the experience of several DR events performed in USC micro-grid we observed that it was impractical for customers to switch between too many strategies during the DR event as this led to additional overhead costs. We modeled this as an additional constraint in the ILP by using a new state transition variable that bounds τ, the number of times a customer can switch strategies between intervals [14]. Note that under this formulation, a customer is likely to have contiguous strategies across intervals.

We use the following ILP to model a Sustainable DR event with strategy overheads.

$$Minimize: \sum_{t=1}^{T} \epsilon_t \tag{6}$$

$$Subject\ to: \mid \sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij}^{t}x_{ij}^{t} - \frac{\gamma}{T} \mid \leq \epsilon_t \qquad \forall t \tag{7}$$

$$\sum_{j=1}^{N} x_{ij}^{t} = 1 \qquad \forall i,t \tag{8}$$

$$x_{ij}^{t} \in \{0,1\} \qquad \forall i,j$$

$$S_{ij}^{t} = \mid x_{ij}^{t} - x_{ij}^{t-1} \mid \qquad \forall i,j,t \in \{2,\ldots,T\} \tag{9}$$

$$\sum_{t=2}^{T}\sum_{j=1}^{N} S_{ij}^{t} \leq 2\tau \qquad \forall i \tag{10}$$

The new constraints to limit the strategy switching are introduced using Equation 9 and Equation 10 where 9 calculates the number of times customer i switches a particular strategy. Equation 10 bounds the total number of times a customer can switch strategies. Since the state variable S_{ij}^{t} counts both switching into and switching out from strategy j, equation 10 uses 2τ as the bound. In our experiments, we fix the value of $\tau = 2$.

3.3.7 Fairness in Demand Response with Strategy Transition Matrix

The customer selection algorithms for Demand Response discussed in the previous sections determine the customer strategy pairs for a DR event without taking fairness into account. This might cause some of the customers to curtail disproportionately more than others. To ensure that the burden of curtailment is distributed evenly among the customers, we defined a notion of fairness in customer selection for Demand Response. We bound the amount of curtailment that can be achieved by each customer. We define a vector $\mathbf{B_t}$ whose ith element denotes the upper bound on the curtailment requested by customer i in interval t.

In the previous section, we bounded the number of strategy switches. In this section, we consider the possibility that due to mechanical constraints, it is not possible for the customers to arbitrarily switch strategies between intervals. To accommodate this constraint, we introduce a concept of strategy transition matrix which guides the strategy transitions for each customer at each interval. Let the number of strategies a customer can adopt is N. We define a terminating strategy as a strategy from which the customer cannot switch to any other strategy until the end of the DR event. Terminating strategy can be used to imply that the customer is now no more a part of the DR event (curtailment value 0). Without loss of generality, let strategy 1 be the default strategy and $N+1$ be the terminating strategy. A strategy transition matrix W^i is an $\{0,1\}^{N+1 \times N+1}$ matrix for each customer i with an element $w^i_{j,k} = 1$ if customer i can transition from strategy j to strategy k and 0 otherwise. At time $t = 0$, i.e. just before the first interval of the DR event, the customer is in strategy 1: the default strategy with curtailment value 0.

Consider a customer with 4 strategies: 1,2,3,4. Let 1 be the default strategy with a curtailment value 0. Let 5 be the terminating strategy. The curtailment value of 5 is equal to that of strategy 1. However, the non existence of any outgoing transition differentiates it from the default strategy. A customer starts with strategy 1 at time $t = 0$. From strategy 1, the customer can either switch to strategies 2 or 3 or remain in 1. From 2 or 3 the customer can either switch to 4 or not switch at all. From strategy 4, the only options are to remain in strategy 4 or switch to the terminating strategy 5. The following matrix represents a valid state transition matrix for this scenario.

$$\begin{pmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

The ILP of Section 3.3.4 can be modified to incorporate fairness and strategy transition matrix as follows:

$$Minimize : \sum_{t=1}^{T} \epsilon_t \tag{11}$$

$$Subject\ to : \mid \sum_{i=1}^{M} \sum_{j=1}^{N} c^t_{ij} x^t_{ij} - \frac{\gamma}{T} \mid \leq \epsilon_t \qquad \forall t \tag{12}$$

$$\sum_{j=1}^{N} x^t_{ij} = 1 \qquad \forall i, t \tag{13}$$

$$x^t_{ij} \in \{0,1\} \qquad \forall i, j$$

$$\sum_{t=1}^{T} \sum_{j=1}^{N} c^t_{ij} x^t_{ij} \leq B_i \qquad \forall i \tag{14}$$

$$\sum_{j=1}^{N} x^t_{ij} W^i_{kj} >= x^{t-1}_{ik} \qquad \forall i, t, \forall k \in \{1, \ldots, N\} \tag{15}$$

$$x^0_{i0} = 1 \qquad \forall i$$

The new Equation 14 added to the SDR ILP ensures that each building participates with an overall curtailment value in the DR event within its curtailment budget. Equation 15 ensures that only valid strategy switching occurs in each interval.

4. EVALUATION

4.1 Prediction Engine Evaluation

A thorough analysis of the various predictions models is performed in [3]. As per the analysis, ARIMA is the preferred model for accurate short term predictions on weekdays.

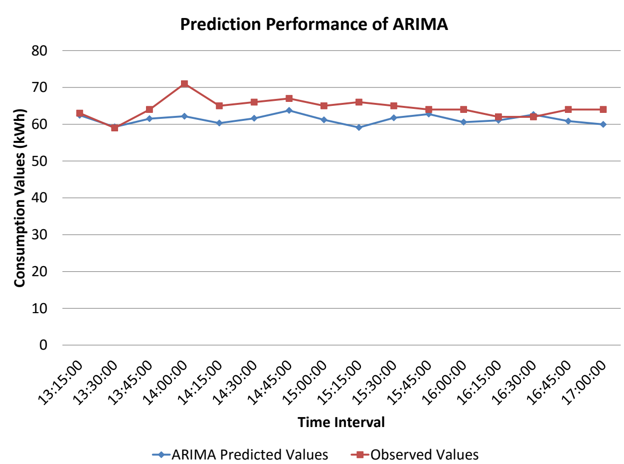

Figure 3: Comparison of the predicted consumption values by ARIMA and actual observed consumption values

In Figure 3, we plot the predicted values by using ARIMA with parameters (p, d, q) as (8,1,4) [3] along with the actual observed consumption values (on a non-DR day). The accuracy of ARIMA shown in the figure is 4.92±3.37%.

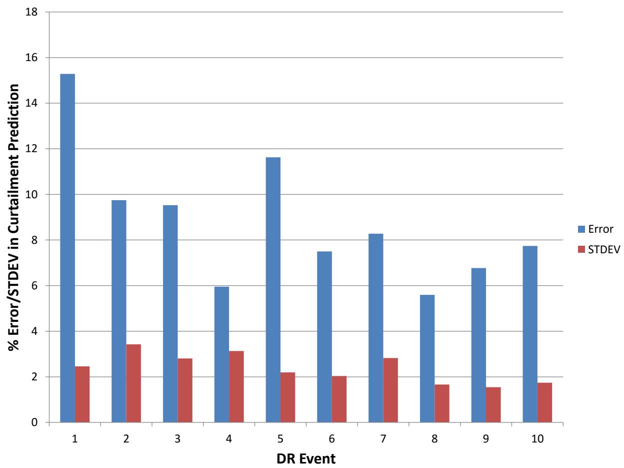

Figure 4: Error/STDEV of curtailment prediction for DR events

In Figure 4, we plot the error/stdev of curtailment prediction for various DR events. For each DR event, we first predict the baseline consumption if no DR event occurs that day. Then we use our Direct Curtailment Forecasting model to predict the reduced consumption for each building-strategy pair. The difference between baseline and the reduced consumption is the predicted curtailment. Once the DR event is finished, we collect the actual consumption which when subtracted by the baseline gives us the actual curtailment value. To plot the figure, we only consider the building-strategy pairs scheduled in the given DR day and calculate the error and stdev accordingly. As can be noted from the figure, the prediction accuracy varies from 5.85±3.13% to 15.28±2.5% across the DR events.

4.2 Optimization Engine Evaluation

To evaluate the performance of the optimization engine, we create a time varying curtailment matrix for a DR event performed on the campus. 28 buildings each with anywhere between 1 to 7 strategies were involved for a 4 hour period with 16 intervals of 15 minute each. A curtailment value of 0 was assigned to a building strategy pair which did not exist. A java implementation of the heuristic was used whereas the ILPs were solved using the IBM ILOG CPLEX software [1].

Detailed experiments for the various optimization modules discussed in this paper can be found in our prior publication [14]. Here, we present just a few results for completeness. Figure 5 shows the results of varying the targeted curtailment from 50 kWh to 1000 kWh. The labels *SDR* refers to Sustainable Demand Response ILP described in Section 3.3.4, *SDR with switch limit* refers to the SDR ILP which considers strategy overheads as described in Section 3.3.6 and *heuristic* refers to the heuristic described in Section 3.3.2. The vertical axis is limited to a maximum error of 3.0 kWh to ensure the readability of the graph. The actual error values are given in the table below the graphs. SDR incurs errors in the range of 0.01-0.1 kWh which in relative terms is 0.004-0.09% SDR with strategy overheads is more restrictive. Thus, it incurs errors in the range of 0.1-0.4 kWh which in relative terms is 0.01-0.4% The heuristic discussed in Section 3.3.2 incurs high errors of 0.7-10 kWh compared with the ILPs, however the relative errors incurred in the range of 0.7-8% is still manageable.

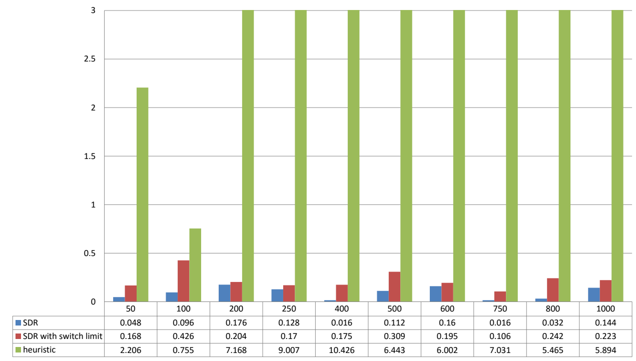

Figure 5: Absolute errors in kWh incurred for a Targeted curtailment in the range 50-1000 kWh

In Figure 6, to emphasize the significance of distributing the curtailment evenly over the entire DR event, we compare the curtailment values achieved in each interval by the ILPs in Section 3.3.3 (referred in the figure with the label *TDR*) and the Sustainable Demand Response ILP described in Section 3.3.4 (referred in the figure with the label *SDR*) for a targeted curtailment value of 1200 kWh for the entire DR interval. TDR ILP incurs an error of 0.002 kWh which is far lower than the 0.031 kWh error incurred by the SDR ILP. However, most of the curtailment is achieved in intervals 10 and 11 and the rest of the intervals have lower curtailment values. The Sustainable DR achieves a curtailment value of around 75 kWh in each interval.

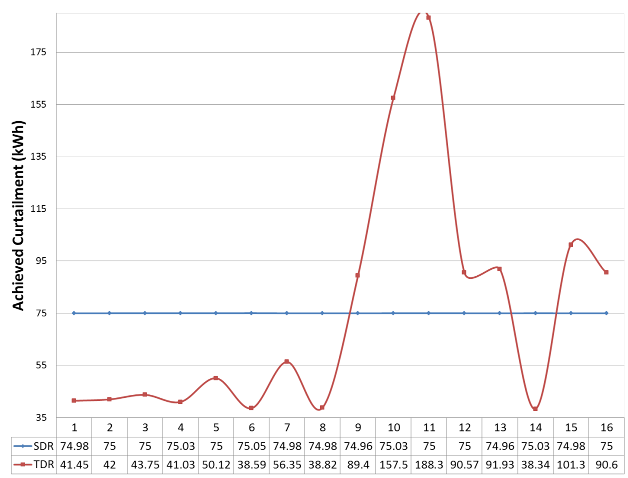

Figure 6: Absolute errors in kWh incurred for a Targeted curtailment in the range 50-1000 kWh

4.3 Overall DR Evaluation

Our prior works have analyzed the accuracy of various prediction and optimization models thoroughly which have also been summarized in Sections 4.1 and 4.2. In this section, we will evaluate how the prediction engine and the optimization fit together to execute a successful DR event.

We will discuss the performance of a DR event performed on the campus. 28 buildings were available for the 4 hour long event from 1 pm to 5 pm. Each building had anywhere between 1 to 7 strategies available to it. A targeted curtailment of 6400 kWh was set. the Policy Engine provided building-strategy pair recommendations to the FMS using the predicted curtailment values. It estimated that a curtailment of 2332 kWh can be obtained using the available building-strategy pairs.

Practical challenges such as increase in temperature above the comfort zone, resident complaints etc. lead to dropping out of certain buildings during the DR event. Sometimes buildings fail to respond to the signals for adopting the suggested strategies. Hence, the actual obtained curtailment value was 2103 kWh for the entire DR event as opposed to the estimated 2332 kWh.

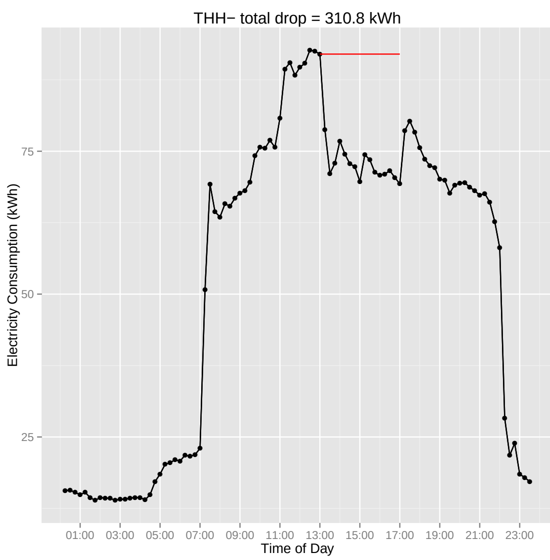

Figure 7: Consumption profile of building THH during DR

In Figures 7- 10, we show the energy consumption profile of a few buildings which achieved the highest curtailment values. The x-axis denotes the time of the day and the y-axis denotes the energy consumption value in kWh. For simplicity, we assume that the consumption in the absence of DR would be the observed value at the start of DR event (1pm). This is denoted by the red line in the figures. The buildings THH, MRF and WPH followed the technique of Variable Frequency Drive Speed Reset (VFD) [20] and obtained a curtailment value of 310, 145 and 98 kWh respectively. The building VKC adopted a combination of Variable Frequency Drive Speed Reset (VFD) and Equipment Duty Cycling (DUTY) [20] and obtained a curtailment value of 169 kWh.

However, not every building achieved the expected curtailment value. Figures 11- 12 show the consumption profile of buildings BHE and DRB which achieved a negative curtailment value. Due to some practical limitations, these buildings failed to adopt the strategies the FMS signaled them to implement.

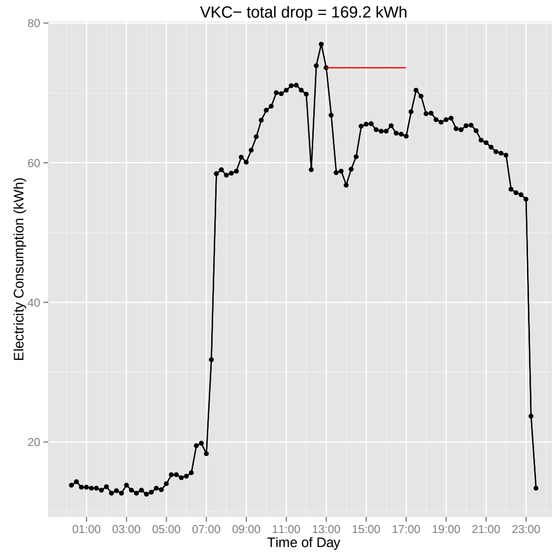

Figure 8: Consumption profile of building VKC during DR

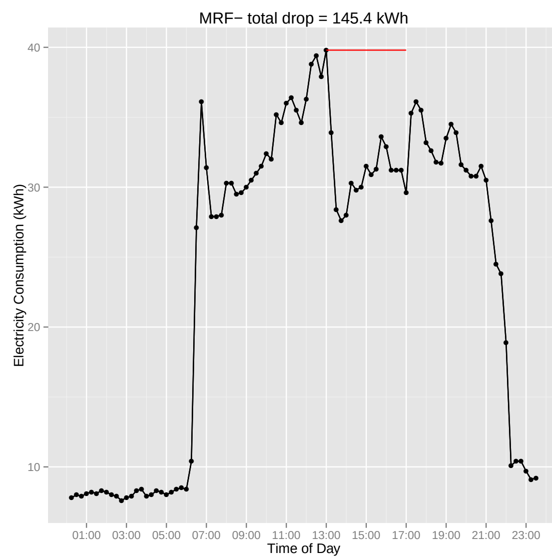

Figure 9: Consumption profile of building MRF during DR

5. CONCLUSION

In this paper, we discussed the implementation of a system which performs automated Dynamic Demand Response (D^2R) in USC microgrid. Leveraging the fine grained data available by the smart meters, our predictive models provide accurate estimation of energy consumption by each building on the campus and achievable curtailment by each building-strategy pair. This information is used by our optimization models to schedule the building-strategy pairs for the DR event in order to achieve the requested curtailment from the grid in a sustainable and fair manner during the entire DR event. The experience gained from such a real world implementation can be used to implement automated DR programs in city scale smart grids.

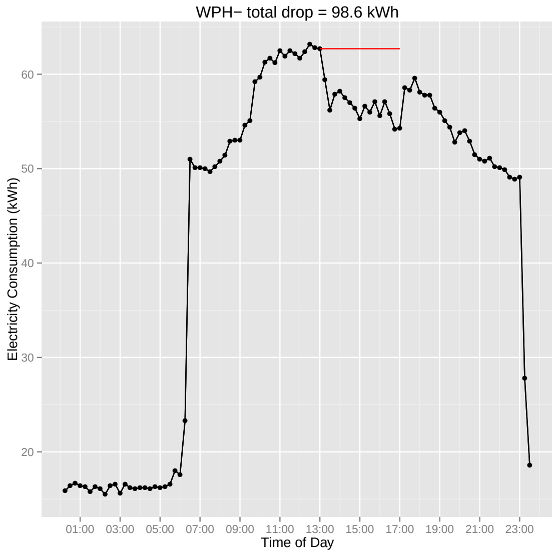

Figure 10: Consumption profile of building WPH during DR

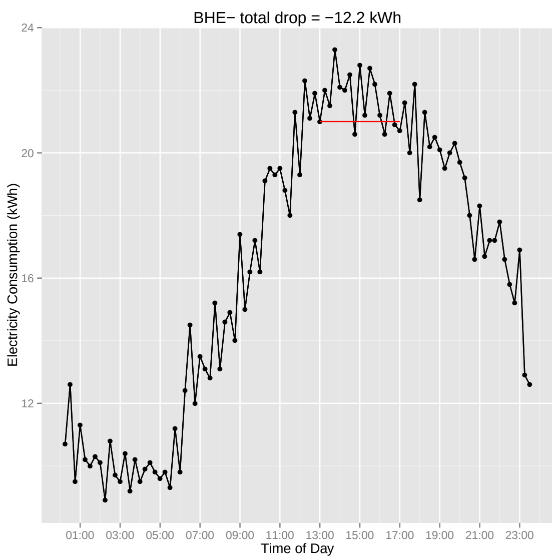

Figure 11: Consumption profile of building BHE during DR

6. ACKNOWLEDGMENT

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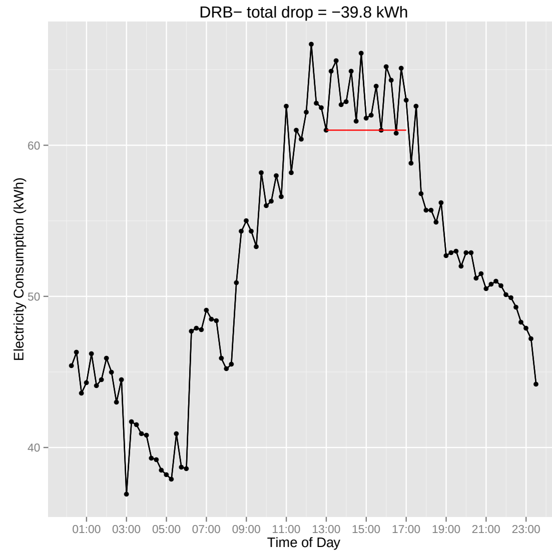

Figure 12: Consumption profile of building DRB during DR

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