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Large Scale Simulation Platform for NODES Validation Study

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1 Introduction

This report summarizes the Large Scale (LS) simulation platform created for the Eaton NODES project. The simulation environment consists of both wholesale market simulator and distribution simulator and includes the CAISO wholesale market model and a PG&E footprint of 25-75 feeders to validate the scalability under a scenario of 33% RPS in California with additional 17% of DERS coming from distribution and customers. The simulator can generate hourly unit commitment, 5-minute economic dispatch, and 4-second AGC regulation signals. The simulator is also capable of simulating greater than 10k individual controllable devices. Simulated DERs include water heaters, EVs, residential and light commercial HVAC/buildings, and residential-level battery storage. Feeder-level voltage regulators and capacitor banks are also simulated for feeder-level real and reactive power management and Vol/Var control.

2 CAISO Wholesale Market Simulator

As indicated in Figure 1, the analysis process includes three basic components: weather and renewable generator models (blue boxes), a production simulation model that identifies the minimum-cost way to operate the power plants (yellow boxes), and a model that checks the stability of the system (green box). The Electric Power Research Institute, the California Energy Storage Alliance, and the Demand Response Research Center provided the data and assumptions describing energy storage and demand response resources that are used in the models. California ISO provided the production simulation model and other supporting data.

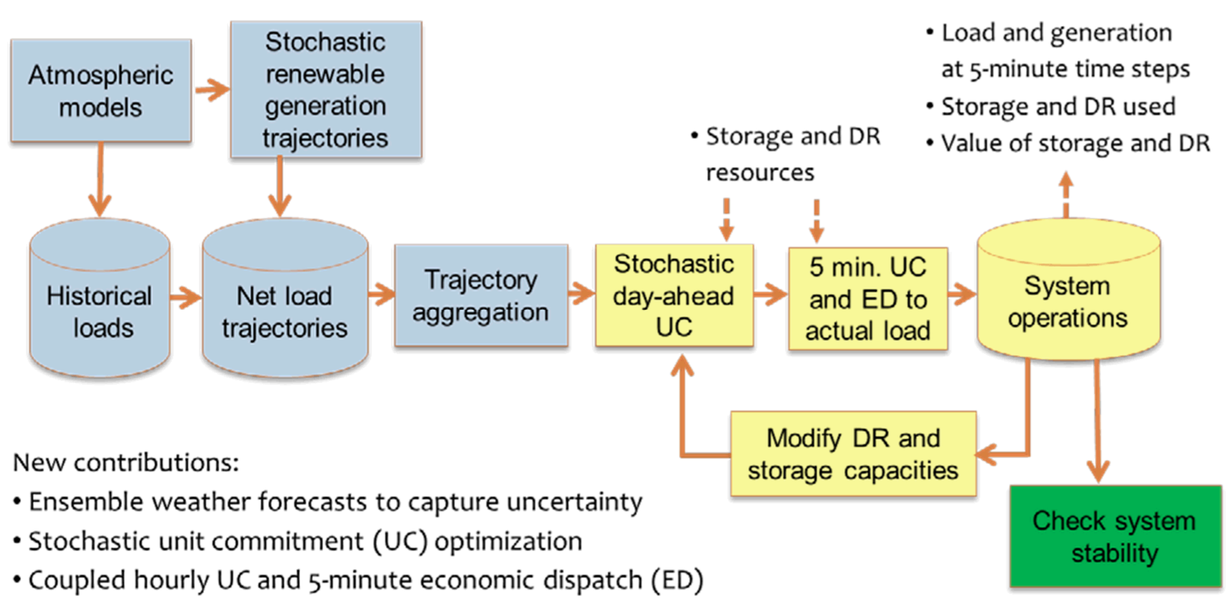

Figure 1. Renewable Generation, Production Simulation, and Resource Evaluation Process

As indicated in the upper left portion of the figure, physics models of the atmosphere are used to develop forecasts of wind speeds and solar insolation throughout the western United States. Weather forecasting is inherently uncertain. This weather uncertainty is represented by a collection of possible wind speeds and solar insolation trajectories (an ensemble). These trajectories are passed to models of wind and solar generators at various locations to calculate power production over time. As indicated in the figure, the atmospheric models also influence the load (for example, higher temperatures lead to higher loads in the summer). Wind and solar renewable generation is subtracted from gross electrical load to get net load that must be met with other power plants, energy storage, and demand response. The trajectory aggregation shown in the figure selects representative trajectories for further analysis. The yellow boxes in the figure describe how the grid would be operated to meet the net load at minimum cost. This is achieved by applying a multistage optimization. In the first stage, units that take a long time to start or stop are scheduled to be turned off or on at various times of the day. The process that determines the least-cost schedule given the uncertain (stochastic) nature of the net load is called *stochastic day-ahead unit commitment* (UC). In the next stage, units that can be started or stopped quickly are committed (5 min. UC), and power levels of all units are determined in a process called *economic dispatch* (ED). This optimization problem was formulated with the PLEXOS modeling software and data sets developed by California ISO for previous renewable integration studies.

Finally, system stability studies are conducted as indicated in the figure. The Kermit code and other analysis software are used to evaluate selected hours of the year in which system stability may be an issue. Data from Kermit models of the WECC previously developed by DNV GL Group are used for this analysis.

2.1 Atmospheric Models

The advanced research dynamical core version of the WRF model is used for this project to generate atmospheric data needed to calculate renewable energy generation from wind and solar resources.

At 16:00 hours the day before each operating day, the model is used to develop an ensemble of possible trajectories of atmospheric conditions over the operating day. These conditions determine the wind power, solar generation, and temperatures over the day.

The atmospheric ensemble forecast system quantifies model uncertainty and quantifies the evolution of the atmospheric probability distribution function (PDF). The two major sources of uncertainty in the day-ahead forecasts are uncertainty about the model physics parameterization and uncertainty about the true initial state of the atmosphere. Both approaches were evaluated for this analysis. (They are not mutually exclusive.) For the reasons discussed below, it was determined that for a day-ahead forecast, the uncertainty due to physics parameters was greater and of higher relevance to the objectives of the present study than the uncertainty due to initial conditions.

The uncertainty over model physics parameterization is converted into an ensemble of weather trajectories using a “multiphysics” analysis. The multiphysics ensemble approach is commonly used to account for model uncertainty and to provide a probabilistic forecast of the dynamically evolving atmosphere. Multiphysics ensemble modeling is based on the realization that no single configuration of model physics is a perfect representation of the atmosphere and that multiple methods to resolve atmospheric processes are needed to adequately describe a forecast PDF. The availability of a large suite of physics options within the WRF model make it ideal for estimating forecasting uncertainty by running multiple forecasts for the same period but with different physics configurations.

The forecast uncertainty due to uncertainty about initial conditions can be analyzed using a multi-initial condition ensemble that executes multiple independent forecast simulations from a suite of plausible atmospheric initial conditions that are based on uncertainty over the background state and meteorological observation error.

The primary reason for using a multiphysics ensemble is based on the observation that the variance in a multiphysics ensemble frequently grows at a rate two to six times faster during the first 12 hours of a forecast than the variance simulated by an initial-condition ensemble. Because the focus of this project is day-ahead forecasting, it is likely that the model output from a multi-initial condition ensemble would underrepresent the uncertainty in the ensemble during the forecast horizon because initial condition perturbations take time to grow and affect the numerical solution. Incorporating the multi-initial conditions analysis would substantially increase computation time and analysis while making little contribution to the analysis of the uncertainties in the day-ahead time frame.

The research team used 30 ensemble members to represent model uncertainty associated with the weather forecasts generated for this project. Each of the 30 ensemble members uses a unique WRF model physics configuration, and all ensemble members are run for the same period to estimate the effect of model parameterization uncertainty on daily atmospheric forecasts. The research team constructed the multiphysics ensemble to vary model physics that will have the greatest effect on forecast uncertainty associated with near-surface winds, temperature, and surface short-wave radiation flux, which are the key atmospheric variables that influence renewable energy production.

Each day, the weather model generates an ensemble of 30 possible weather trajectories that could have been realized on that day in 2005. However, only one weather trajectory occurred in 2005 each day. Synthetic observations are generated by nudging the model to better fit the measured data. Hence, the synthetic observations provide the best estimate of the actual weather realized in 2005. Comparison of the synthetic observations with the 2005 measurements provides one approach for validating the model.

The ensemble of forecasts can be validated by comparing the ensemble to measurements of the realized weather. If the measurements are contained within the envelope of the ensemble, there is an increased level of confidence that the ensemble accurately represents the 2005 historical weather patterns and the uncertainty in these patterns.

Some 2005 temperature and wind speed measurements are available to validate the model. However, none of the measurement locations correspond to the exact center of a grid cell where the weather conditions are predicted by the model. In addition, few wind measurements at rotor hub height in the right locations are available to validate the wind speed forecasts. For a given set of measurements, the nearest grid cell in the model at the nearest height is used for comparison with the measurements. Hence, some error is introduced into the validation process due to the lack of data in required locations.

2.2 Load Data

Load forecasts developed to support California ISO's 33 percent renewable integration study were acquired for use in this study. Because the California ISO study did not include the use of weather ensembles and related effects on renewable generation and load, some adjustments to load were necessary.

The PLEXOS model used in the analysis requires load data for every WECC region at two time scales. A set of day-ahead hourly load forecasts are required for the stochastic unit commitment algorithm in PLEXOS, and five-minute average loads are required for the economic dispatch and short-term unit commitment algorithm.

The temperatures in each of the 30 hypothetical weather trajectories generated by WRF with multiphysics modeling can influence the loads. To produce consistent pairs of renewable generation and load trajectories, the team adjusted the base case load in California ISO's PLEXOS model to reflect the deviations from the realized temperatures associated with that base case load. This temperature adjustment was performed only for the loads in California. Out-of-state loads were taken directly from the California ISO PLEXOS model.

This general approach used for these load adjustments is as follows:

1) Use historical load data to calibrate a set of equations that capture how loads in each of the regions in each hour of the day change with temperature.

2) Calculate an average temperature for each period, each region, and each of the 30 trajectories in the weather ensemble

3) For each weather trajectory and region, calculate the temperature difference between the average temperature for that trajectory and the realized temperatures corresponding to 2020 loads (delta T for trajectory and period).10F11

4) Use the delta T term and the equations from Step 1 to calculate an adjustment to load for each period, trajectory, and region.

2.3 Clustering and Selection of Trajectories

Previously it was described how the WRF and multiphysics models generate an ensemble of 30 weather trajectories that are converted to net load using models of renewable resources and perturbations of load caused by the weather. Conceptually, these 30 net load trajectories could be passed to a production simulation code to perform stochastic unit commitment optimization for the day-ahead market. As discussed previously, the production simulation model used for this study is California ISO's 42 node, 104 line, and 2,400 generator PLEXOS model of the WECC. Experiments with this PLEXOS model indicate that run time and memory usage become excessive when more than six net load trajectories are included in the problem. Therefore, it was necessary to reduce the ensemble of 30 trajectories to a computationally feasible set of five or six that represent the uncertainty and variability in renewable generation and load.

The general concept used for reduction of the ensemble is to include a few trajectories that stress the system (for example, high net load ramp rate), each with an appropriate probability weight (such as, 1/30 for a single selected trajectory). Statistical clustering methods are then used to gather the remaining trajectories into like groups and to select a representative trajectory from each group. This process reduces the 30 trajectories to 5 or 6. Because 30 trajectories are sampled and the outlier of this sample is selected (top 3.3 percent of the sample), the range of uncertainty captured by this process is conceptually similar to the 95 percent confidence limits used in previous California ISO renewable integration studies.

Statistical clustering methods group observations (scalar- or vector-valued) into clusters, with each cluster consisting of observations that are more similar to one another than to observations in other clusters with regard to some specified characteristics. These characteristics are relevant summary features of each observation. In this case, the observations are the 30 individual 24-hour net load trajectories, and the features are quantities that the research team deems important for capturing the amount of stress any particular trajectory may have on the system. The goal is to use a clustering method to obtain six or fewer clusters and then select one representative trajectory from each of the clusters. By design, each trajectory selected in such a way represents the respective cluster in terms of the specified features. A weight proportional to the size of the cluster is then assigned to each chosen trajectory, and these trajectories, along with associated weights, can then be used as inputs to the stochastic unit commitment optimization algorithm in the PLEXOS model.

K-means clustering is one of the most commonly used clustering algorithms due to simplicity and effectiveness. It assigns each observation to the cluster whose mean is closest to the observation. (This is a particular way to measure similarity within a cluster.) K-means is an iterative method because once an observation is assigned to a cluster (there are several schemes to initialize the clusters), the mean of that cluster is recomputed, and cluster assignment is updated. This is repeated until cluster assignment no longer changes from one iteration of the algorithm to the next.

2.4 Production Simulation Modeling

As indicated in Figure 1, the production simulation model uses a two-stage optimization procedure to find the least-cost way to operate the system. The first stage finds an optimal unit commitment (on or off state of the resource) schedule for fast- and slow-start units using hourly forecasts of net load. The second stage assumes the unit commitment states of slow start units are fixed and finds an optimal unit commitment schedule for fast-start units and economic dispatch (power level) schedule for all units that minimizes overall cost of meeting system load and reliability constraints. All resources and the corresponding variable costs, including demand response and storage, are taken into consideration by the optimization code. The role and value of demand response and storage depend strongly on the set of conventional units that have been committed and dispatched at any given time.

As shown in the figure, the output of the production simulation model is the system state (generator output, hydro reservoir and other storage levels) at each time interval in the year. In addition, the production simulation model provides the value and usage of demand response and storage resources at each period. The value estimate provided by the model is based upon the resources that demand response and storage displace. The output of the production simulation model is also provided to a system stability analysis code that computes response of the system to potential transients, such as loss of a generator or transmission line. This response must meet stability conditions imposed by system regulators.

2.5 Stochastic Unit Commitment

As indicated, the costs of starting units and operating them at the minimum stable levels must be accounted for in the simulation. The decision to start or stop a unit may be made at each hour of the day. Furthermore, this decision may be constrained by the previous operating history of the unit because many units have minimum up and down times. For some of the units—particularly the larger ones—the time required for starting them is long enough that the schedule to start them must be specified a day ahead of time. The California ISO unit commitment model includes a suite of additional constraints relevant to operating the California grid, including import limitations, hydro pumped storage limits, ramping limits, and load-following limits.

The solution of the unit commitment optimization problem involves specification of the state of each generator at each hour of the day. This state is a binary condition; the unit is either on or off. In general, optimization problems with such integer variables pose daunting computational challenges. Solution procedures usually require an extensive search through a large space of possible solutions and can require implicit enumeration of all possible states of the system.

When multiple possible net load scenarios must be taken into consideration, the problem is further complicated by the need to solve a "stochastic" unit commitment problem. The solution involves finding a single unit commitment schedule that minimizes the expected system cost over the set of net load scenarios that may be realized. For the selected unit commitment schedule, the cost of operating under each of the scenarios is multiplied by the corresponding probability to obtain the expected system cost.

2.6 Interleaved Timescales

For each period, the power level of each unit that is on must also be specified. Specification of power levels at the one-hour intervals used for the unit commitment decisions does not provide sufficient resolution to evaluate load-following resources. Hence, there is a need for multiple timescales in the model. The most recent version of the PLEXOS software provides this capability. The logical relationships among the model timescales are illustrated in Figure 2.

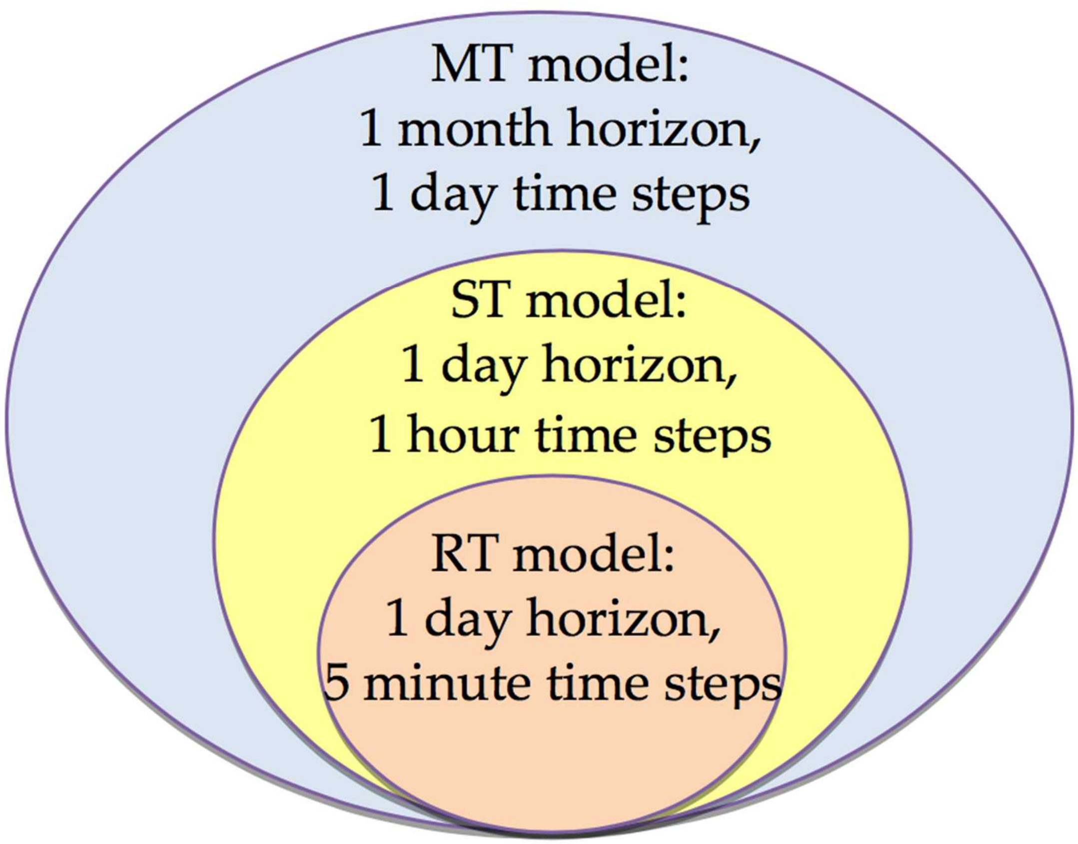

Figure 2. Time Horizons of the PLEXOS Model

In this configuration, a medium-term (MT) model is first run on a monthly horizon to determine hydro resource targets for each day. Next, a daily short-term (ST) model is run to compute an hourly stochastic unit commitment schedule for long-start units, using the set of possible net load scenarios. Interleaved with each of these models is the real-time (RT) model with 5-minute time steps for economic dispatch. This dispatch employs the net load scenario computed using the "synthetic observations" of weather. The three models are co-optimized mathematically, and relevant parameters are passed back and forth between different time horizons to ensure integrity of the resulting solution.

Finally, the production simulation model calculates revenues and variable operating and maintenance costs of operating the facilities. It also includes CO2 emissions costs of $36/ton CO2. This information, combined with capital and fixed operating and maintenance costs, will help investors and ratepayers decide what types of resources should be developed. Some simple financial models were used to estimate return on investment and net present value of the storage technologies modeled. Capital structure, cost of capital, and other financial parameters are drawn from previous studies. For demand response, researchers calculated the maximum capital costs that would be justified by the revenue streams that would be realized. Sensitivity studies on discount rates and other key parameters are conducted.

2.7 Regulation and System Stability Modeling

The results of the PLEXOS simulation is a sequence of generator commands that determine which generators are on and off, which generators are providing reserves, and how much power each is generating for each 5-minute time step. This dispatch is determined by minimizing cost. However, there is the potential for the set of generators dispatched by PLEXOS to not function well when operated at a second-by-second basis. The power grid is required to balance power and maintain frequency on a second-by-second basis under normal operating conditions and in unusual events that will inevitably occur. This balancing process under normal conditions is referred to as *regulation*, and the system response after an unusual event is referred to as *stability*.

2.7.1 Regulation Analysis

LLNL, in coordination with DNV GL Group, has a pair of simulation environments that can simulate the operation of the regulation resources on the system and gauge the effectiveness at performing this function. The KERMIT software from DNV GL was developed for this purpose. A KERMIT model has been calibrated and tuned for the Western Interconnect that can provide detailed information on system regulation when new technologies such as demand response and storage are widely deployed. However, due to the development in the Simulink software environment and the detailed nature of its operation, performing a large number of tests with that software is impractical given the setup time, manual execution steps, and length of run time. These limitations made it unsuitable for the large number of tests required in this project. Therefore, a faster and simpler version in the C++ computer language was developed. This version lacks many of the sophisticated dispatch and simulation capabilities in KERMIT but maintains the same core simulation capability. The new C++ version can also be executed in an automated fashion at much higher execution speeds.

KERMIT is used to calibrate the faster simulation model. After calibration of the C++ simulator, the full year of PLEXOS results is analyzed to gauge the performance of regulation resources over the entire year. The system is evaluated according to a number of operating criteria developed in conjunction with DNV GL. These criteria include statistics on the area control error (ACE), grid frequency, CPS1, and CPS2. Also, a set of metrics is used to evaluate the ability of storage and demand response technologies to provide regulation capability.

On a subset of days, a range of regulation portfolios is tested. These portfolios include all storage, demand response, and conventional regulation resources, as well as various combinations of the resources. These tests provide a basis for determining the effectiveness of the various technologies at providing regulation in a realistic grid scenario for 2020 and a basis for comparing one technology to others. Several selected scenarios are also run using KERMIT to verify the results and provide a finer grain of detail for the results.

2.7.2 Stability Analysis

The grid must also be stable in the event of a sudden shock to the system. In conditions of high renewable penetration, it is possible to foresee situations in which the amount of conventional spinning resources shrinks to a potentially unstable level. Such events include large generators going offline suddenly or transmission lines faulting suddenly. To evaluate system stability, the team selected scenarios that exhibit extreme operating conditions on the grid from the result of the PLEXOS output. These scenarios are run with the regulation model and a shock applied to the grid such as a major generator going offline, or a transmission line fault. The response of the system is evaluated for any system blackouts, maximum frequency deviation, and recovery time as indicated in Figure 3. Specific emphasis is placed on the performance of nonconventional resources such as storage and demand response under these conditions. The intention of these analyses is to gain insight into the performance characteristics of storage and demand response and potentially problematic situations.

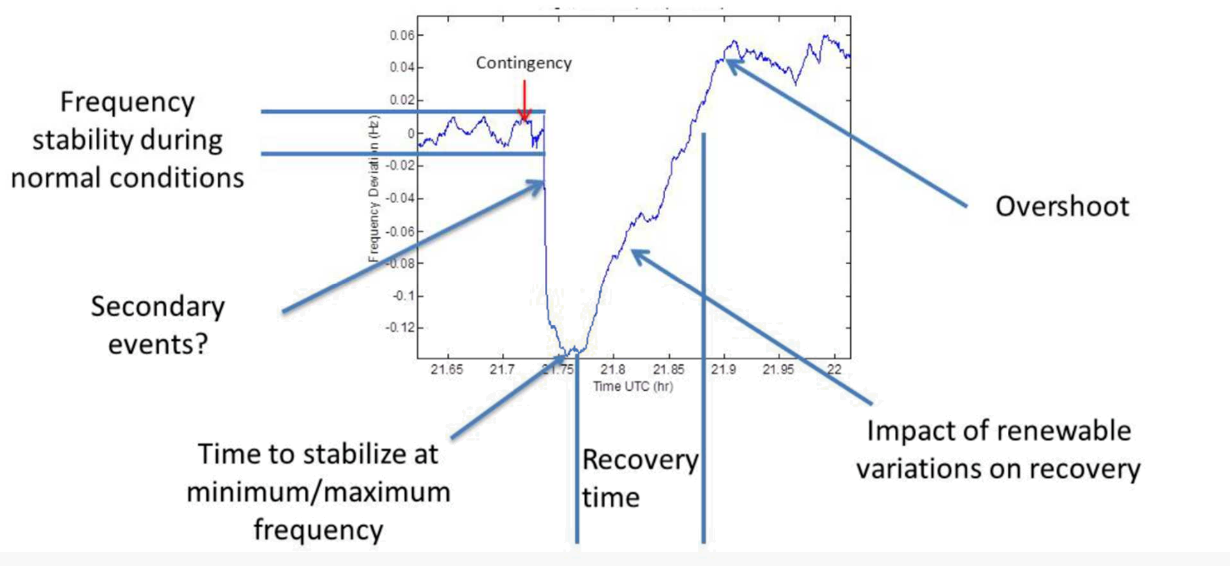

Figure 3. System Stability Analysis

The intention of the stability and regulation analysis is to evaluate the effectiveness of newer resources such as demand response and storage to provide critical grid services and to maintain stable grid operations in time frames shorter than the economic dispatch interval.

3 Distribution grid (PG&E model) with end-use loads simulation

The PG&E footprint of 25-75 feeders are created based on 15 PG&E feeders modeled using GridLab-D. To scale up the DERs coming from distribution and customers, LLNL team has also developed detail dynamic loads to represent different scenarios of deploying distributed energy resources (DER). The simulator can simulate more than 10k individual controllable devices including detail load such as plug loads, water heaters, HVAC of residential/commercial building, lightings, electric vehicles recharging, residential roof installed PVs, centralized and decentralized battery storages etc. Feeder level Voltage/VAR control and demand response will also be simulated in the model. Furthermore, a part of transmission system (including Tesla Substation) is chosen to be modeled to study the interactions between transmission and distribution systems.

3.1 Distribution grid simulation tool

As renewable energy of grid grows up quickly, distributed energy resources (DER) of distribution grid, such as wind farms, PVs farms and roof PVs, centralized or distributed battery storages and significant expansion of electric vehicles has already influenced more and more grid operations, with some favorable areas already experiencing high penetration levels of smart inverters with PV generations. In control field, demand response, voltage & reactive power control, smart electric vehicles remoter control recharging all require distribution systems could response transmission grid operation rapidly and improve the whole grid operation. So distribution grid simulate should play more and more important role in power grid research. GridLAB-D ™ is used for distribution system simulation in this project. This open source software is developed by Pacific Northwest National Laboratory (PNNL) in collaboration with industry and academia through funding from DOE and incorporates advanced modeling techniques with high-performance algorithms to deliver the latest in end-use load modeling technology.

3.2 PG&E distribution grid feeders

The 12 representative PG&E distribution feeders modeled in GridLab-D are showed in table 1.

Table 1. PG&E 12 Distribution Models

Index	Model Name	Total Objects
1	AL0001	3260
2	AT0001	1692
3	BR0015	631
4	BU0001	509
5	D0001	1731
6	HL0004	5869
7	MC0001	3415
8	MC0006	5143
9	MO0001	3810
10	OC0001	3070
11	PL0001	821
12	TMP0009	16060

In addition, another three PG&E feeders (Carbona 1101, Lammers 1101, and Tracy 1106) are modeled in GridLab-D for transmission and distribution co-simulation purposes.

- **Carbona 1101**

Carbona 1101 is a radial distribution (12KV) feeder located in southern part of Tracy. This feeder comprises 718 nodes and 815 sections. There are 273 spot loads, 422 overhead lines, and 298 cables. Figure 1 shows a pictorial view of this feeder.

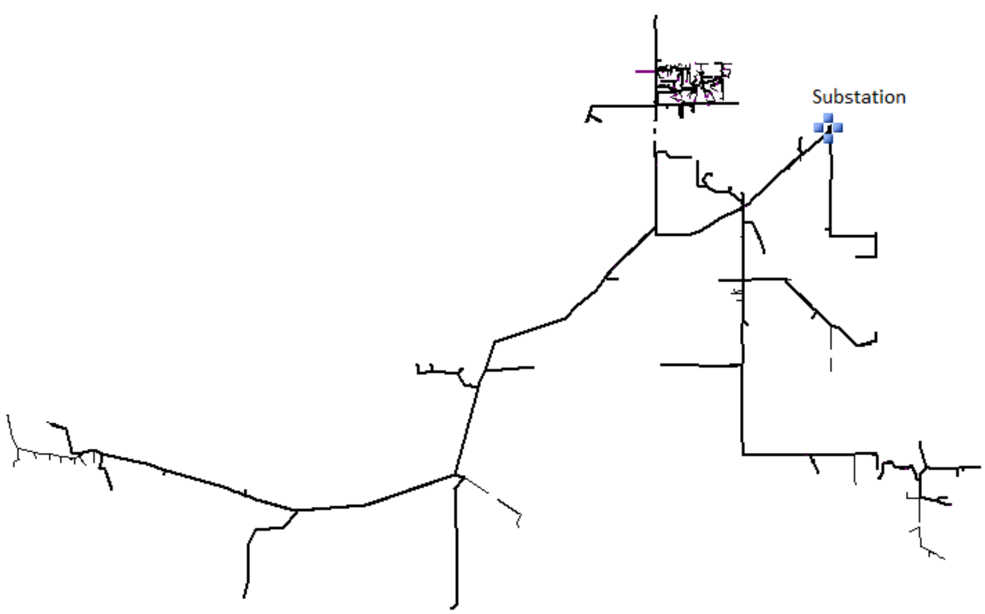

Fig. 1. Pictorial view of Carbona 1101 feeder

In addition, there are 9 shunt capacitors, a regulator, and 88 PV units aggregated in this feeder.

- **Lammers 1101**

Lammers 1101 is a radial distribution (12KV) feeder, located in south-west of Tracy (between Tracy distribution feeders and Tesla substation). This feeder contains 287 nodes and 300 sections. There are 86 spot loads, 189 overhead lines, and 101 cables. Furthermore, there are 8 shunt capacitors, a regulator, and 2 PV units accumulated in this feeder. Generally, this feeder is smaller (in size) than the other two previously studied feeders and it can be used as a good case for smaller feeders in the distribution grid. Figure 2 shows one-line diagram of Lammers 1101 feeder in CYME.

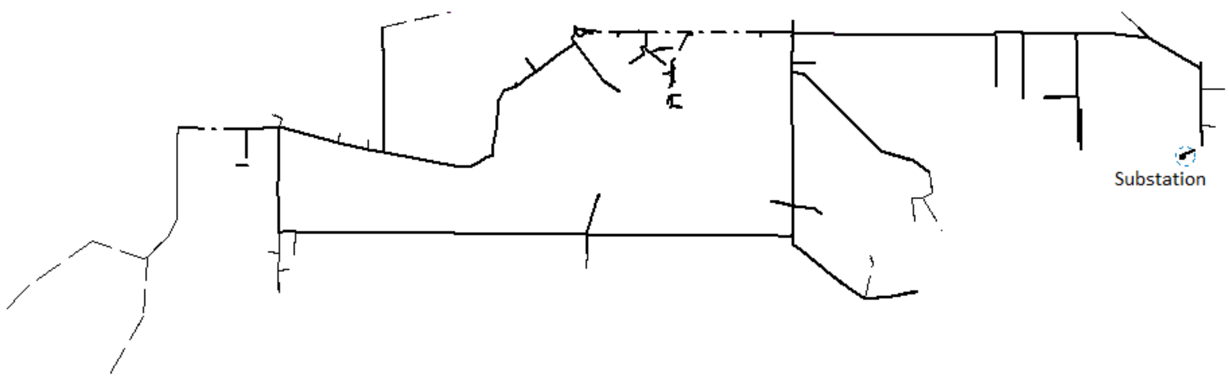

Fig. 11. One–line diagram of Lammers 1101 feeder

- **Tracy 1106**

Tracy 1106 is also a radial distribution (12KV) feeder located in Tracy. This feeder consists of 750 nodes and 811 sections. There are 342 spot loads, 501 overhead lines, and 259 cables. Furthermore, there are 8 shunt capacitors, 2 regulators, and 43 PV units accumulated in this feeder. In this section, similar to previous section. Figure 3 shows one-line diagram of Tracy 1106 feeder.

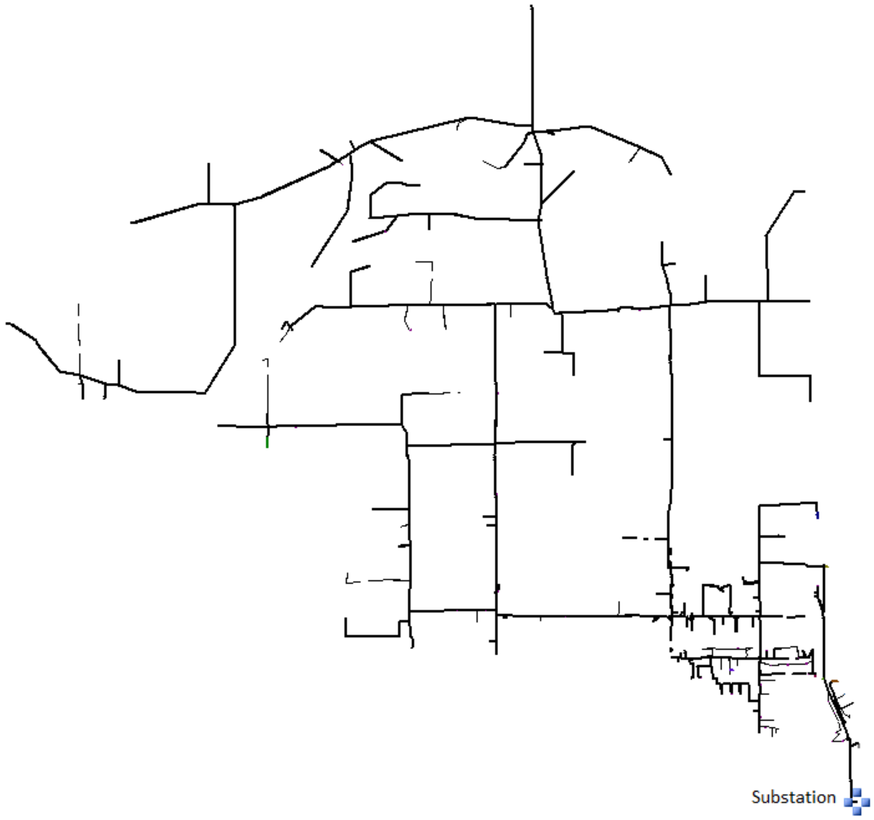

Fig. 3. One–line diagram of Tracy 1106 feeder in CYME

3.3 DERs modeling

Total 102 GridLab-D models are developed for this project to represent detail end-use load models with DERs. These models can be categorized into four types:

- Large scale roof PVs and PVs farm simulation models
- Electric vehicles behaviors and recharging simulation models
- Three types demand response models
- Smart Inverters for Volt/VAR Control

IEEE13 GridLab-d model is a base model to be modified to connect DERs. Below figure shows the IEEE13 GridLab-d model has 13 nodes, total 1704 objects which support 360 houses with behind meter objects. The events simulation is driven by "Sacramento" weather file and simulation time is from 13:00 PM to 16:00 PM. The IEEE13D model output load range is from 1 MW to 1.8 MW. There are one regulator and two capacitors installed on the model. The behind meter residential buildings' floor area is randomly setup from 1700 to 2800 square feet. Cooling temperature set point is randomly setup from 70 to 76 with 5-degree band. The water heater capacity is 4 kW, air conditioner's rate power is 5 kW, and another appliance load of house is about 2 kW. All appliances loads are controlled by schedule time file.

Total 360 sets Solar PV panels with inverters, 40 Electric Vehicles, 6 Storage Batteries with inverters, and 360 sets Demand Response Controllers are designed and could be selected to connect to this IEEE13.

3.3.1 Large scale roof PVs and PVs farm simulation models

Solar generation varies only relatively slowly and predictably as the sun moves across the sky on a clear day, and it would be relatively easy to make compensating adjustments with conventional equipment. On a cloudy day, however, solar output can change rapidly on time scales of seconds and minutes. Maintaining voltage levels under these conditions is more challenging and attempting to do so with conventional electromechanical equipment can lead to increased maintenance and reduced service life of the equipment.

There are about 40 GirdLab-D distribution models built for this research with 10%, 30%, 50% , 75% and 100% ratio of residential buildings' roofs. These models simulate how system load and voltage change and impact power flow of grid system when cloud passing those PVs. The 15 PG&E distribution feeders constant load are also replaced by variable residential buildings with roof PVs for this project.

3.3.2 Electric vehicles behaviors and recharging simulation models

Plug in electric vehicles (PEVs), both pure electric and hybrid have been encouraged auto-manufactures to develop. California has already established itself as an early adopter of the new technology. As national and California's PEVs number increases, vehicle recharging will represent an increasing share of the total load and loads will become increasingly more subject to being influenced by pricing strategies and customer choices. By 2020, as huge load and storage resource, PEVs could either create significant problems or represent an overall benefit to the electric grid, largely depending on how well utilities would manage customers recharging vehicles.

The 12 Gridlab-D electric vehicles behaviors those commute distance varies from 5miles to 60 miles single trip and recharging simulation models are built to research how PEVs recharging methods impacts transmission grid operations.

3.3.3 Three types demand response models

Demand response provides an opportunity for consumers to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage during peak periods in response to time-based rates or other forms of financial incentives. Demand response programs are being used by electric system planners and operators as resource options for balancing supply and demand. Such programs can lower the cost of electricity in wholesale markets, and in turn, lead to lower retail rates. GridLab-D has the three primary types of demand response DR control method: Direct load control, Thermostat passive price control, and Duty cycle control. In these simulation models, end-use distribution house loads operate on a typical IEEE 13 bus distribution system.

The 30 demo models have 360 to 2000 residential houses. Electric lighting, water heaters, and HVAC systems are modeled and controlled as house standard loads. The electric vehicles are used as distributed energy storage. PV panels are installed as distributed generation. Direct load control, Thermostat passive price control and Duty cycle control methods for HVAC are all simulated in these Models. In this stage, the HVAC system and electric water heater are controlled by Time Of Use (TOU) pricing in this model. The passive control uses “ramp” mode that specifies the slope of the linear control algorithm as a function of the average price, the current price, and the standard deviation from the average, and determines the controller’s operation.

3.3.4 Smart Inverters and Co – simulation for Volt/VAR Control

Regulators and switched capacitors are commonly used devices for Volt/VAR control. Large-scale PV penetration will cause system frequently regulations. Smart inverters are capable of operation at any desired phase angle with respect to the grid, providing significant opportunity for Volt/VAR control. With appropriate algorithms, PV inverters should be able to play a significant role in reducing voltage variations and mitigating variability of PV power output. Smart inverters with programmable phase control and low - voltage ride - through capabilities will offer the prospect of significant new opportunities for Volt/VAR control, outage management, and other operational control issues. Smart inverter models and studies are required to determine the control algorithms that can best improve voltage control under high penetration of PV while minimizing or eliminating undesired impacts on distribution systems. Now, Co – simulation plays an important role in “smart grid” which contains sensor networks, distribution devices, communication links, and automatic controls In particular, communication latency can have a strong impact on whether automatic controls can react rapidly enough to perform properly. Co - simulation capability is likely to be increasingly useful and important as distribution automation adds ever more features that are advanced.

Theses 20 Gridlab-D smart inverter simulation models are built to research how to use smart inverters and co-simulation for VOLT/VAR control and impacts transmission grid operations.

3.4 PG&E distribution feeder model with DERs

The PGE_AT0001_v1_glmfile model has 316 constant load nodes those total load is 12.447 MW. There are 34 three phases load nodes are selected to connect behind meter residential building loads based on

IEEE13 distribution models (Fig.4) shows the IEEE13 distribution module. Fig.5 shows the detailed behind meter IEEE 13 model in which there are 360 residential buildings and 2300 objects. In the PG&E model, could select from 0 to total 34 IEEE13 modules connected to the distribution system. The simulation time step and the simulation recoding time step are both 600 seconds.

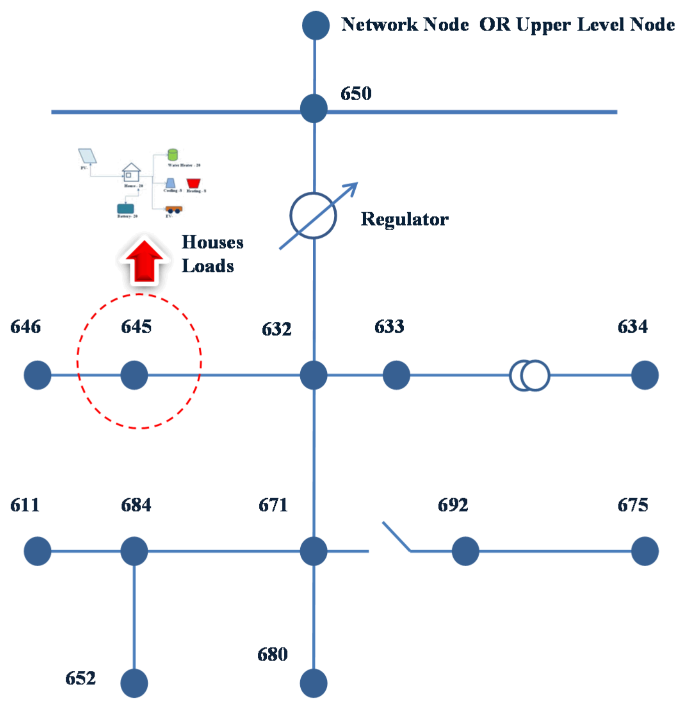

Fig. 4 IEEE13 distribution Module

In order to connect PG&E test model, there are three levels : 7200, 2400 to 120 voltage in the IEEE13 model. The load range of each IEEE13 module is from 700 KW to 2.3 MW in a typical summer day (July 4) to match the original PG&E model. There are air conditioner, lighting, plug-in and water heater appliances in each residential building module. All loads of residential buildings are controlled by schedule files.

The building floor area of model is randomly from 1200 square feet to 3200 square feet. The air conditioner is electric supply and heating system is natural gas. Building temperature set point is 70-77 degree randomly setup and control dead band is three-five degree randomly. Fig.6 shows the 24 hours load range of the IEEE13 distribution model.

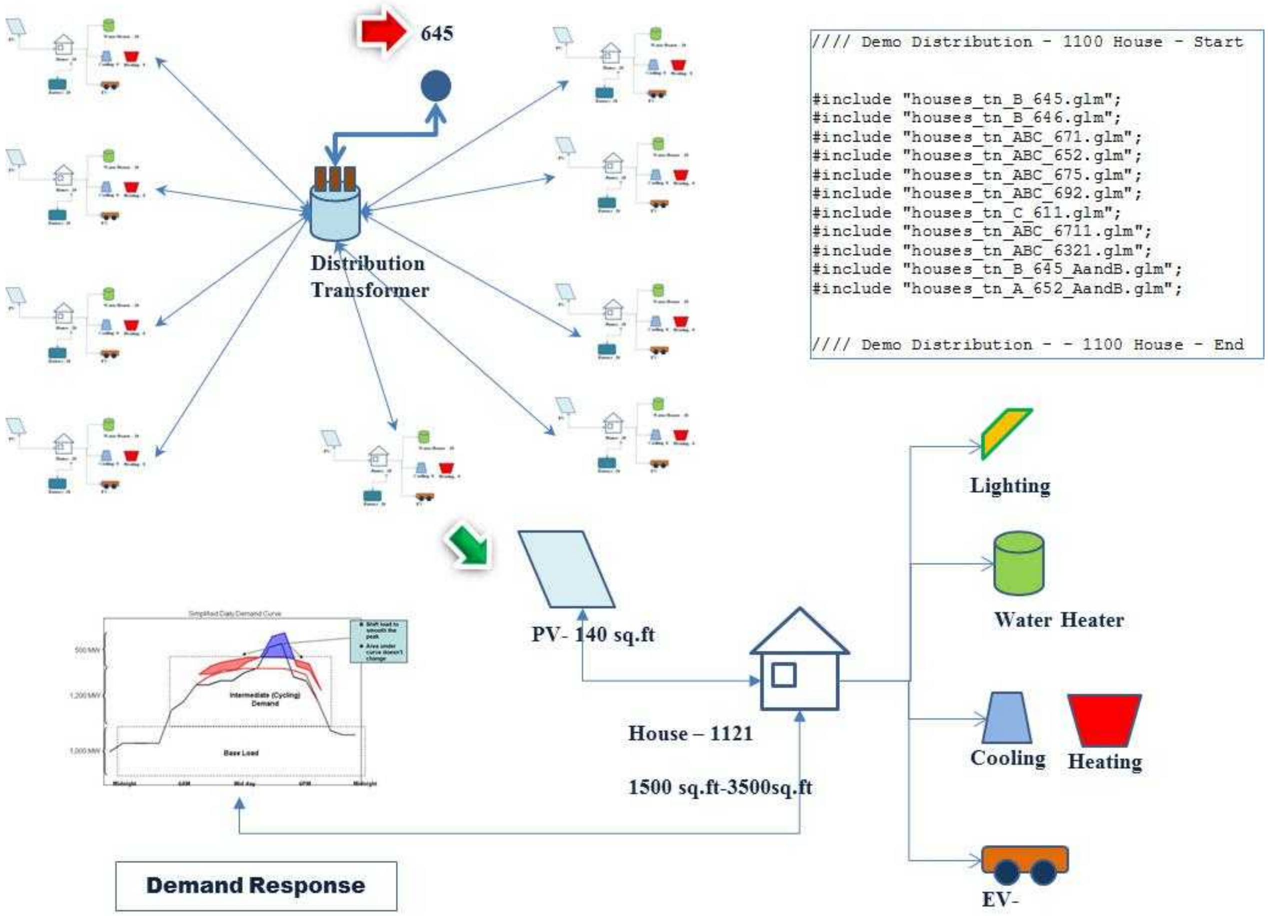

Fig.5 The detailed behind meter End-use house load and control simulation

The test case was built on the IEEE 13 distribution circuit. It has 360 houses with total 700KW ~ 1,300KW residential load. A 800KW commercial building load was added to this case. We added additional distributed generation to the IEEE-13 test case, 2 Diesel generators - 500KW each, 2 micro wind turbines - 1.5KW and 3KW, A 200KW solar farm, 6 batteries - 5KW each.

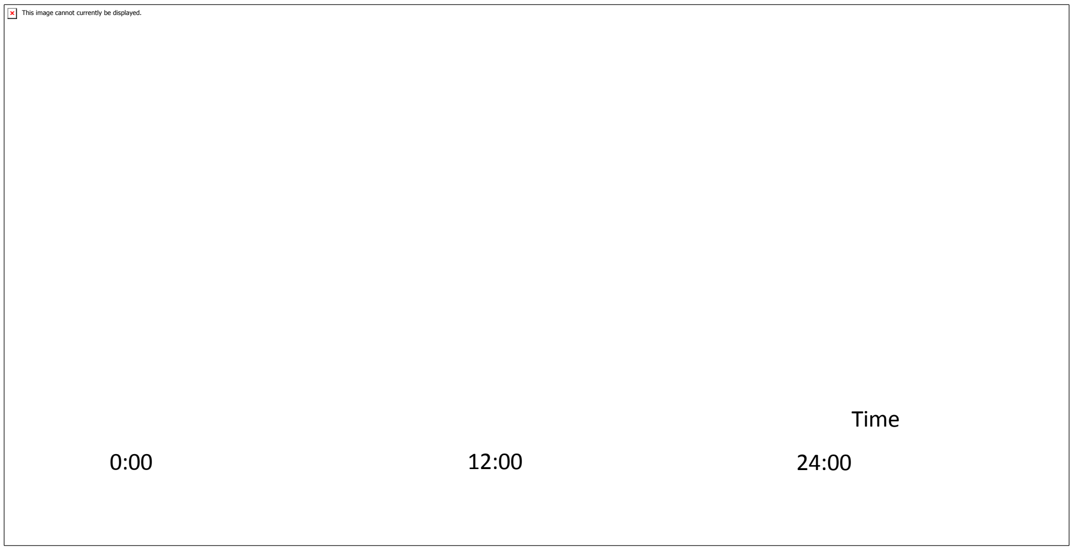

Fig. 6 Load range of IEEE13 distribution Module in 24 hours

3.5 Simulation results

This GridLab-D simulation model has about 1000 houses with load, PVs and EVs. Fig.7 shows the distribution system structure. It has three levels from substation and two level transformers. Red rectangles mean distribution system is feeding power to all house loads. The climate module provides an interface that other objects may use to include weather data in their calculations. Objects such as houses and buildings rely on these data to factor outdoor weather into their calculations for internal temperature. The climate data includes temperature, humidity, and solar radiation, which is used to calculate temperature gain that is the result of heat gained from direct exposure of a surface to sunlight. Green of rectangles mean distributed generations of houses are feeding power back to power system. Appliance loads of houses such like water heater, lighting, HVAC system are simulated in this demo. PV panel is simulated as distributed generation. Electric vehicle is simulated as appliance load but not energy storage in this stage.

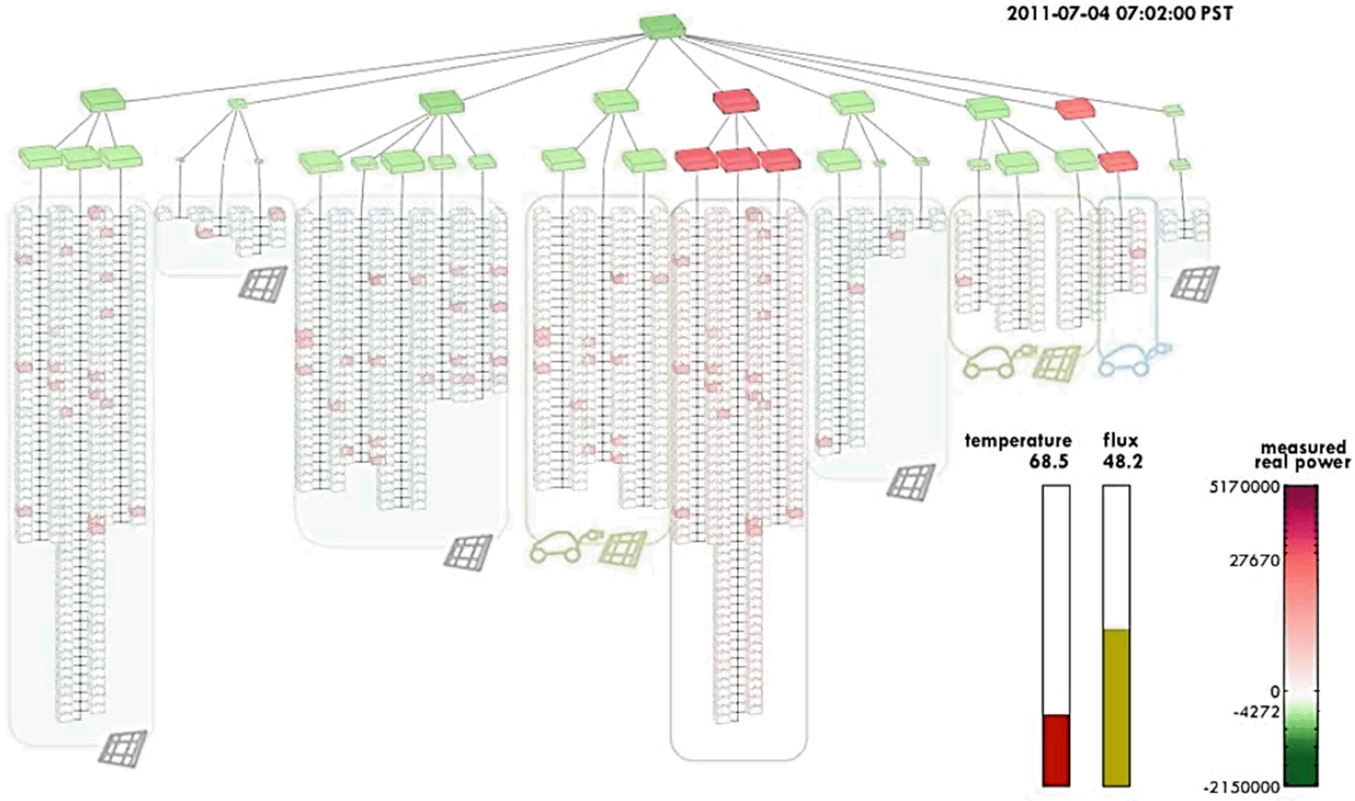

Fig. 7 Distribution End-use house loads module visualization simulation

3.5.1 Electric Vehicles Control simulation

The Electric vehicle recharging process is also simulated with this demo. The EV-charger object can be put on a schedule to control when it is at home, work, or on a trip. This can be done by using a schedule for the p_go_home and p_go_work properties (only control when it is at home or work) or by using the demand_profile property. Fig.14 shows EV-charger demand_ profile which represents EVs probability time of recharging. Four different color curves show “arrive home”, “departure home”, “arrive work” and “departure work” probability time. Ev-charger objects will be operated by these curves to control EVs recharging process by a random function.

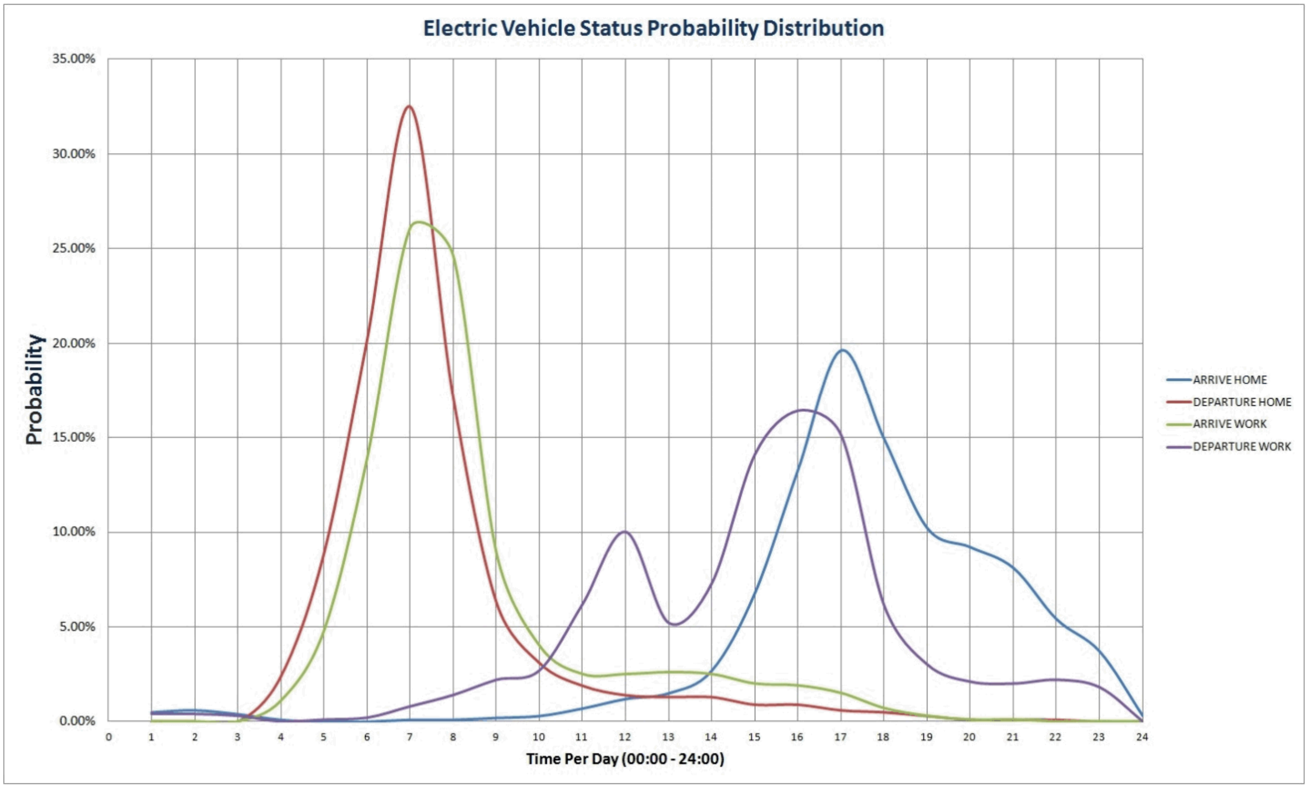

Fig. 8 Electric Vehicle Status Probability Distribution for Recharging

3.5.2 Volt VAR control simulation

Recently there has been increased interest in the area of voltage control and power factor correction for distribution system operations. This is partially due to the inefficiencies that have historically existed in distribution planning and operations. This use case examines methods of voltage control and power correction and their effects on their respective feeders, as well as the transmission system. In GridLab-D, the Volt/VAR object coordinates selected regulator and capacitor objects on the system. Using voltage measurements at node object points, the Volt/VAR object tries to maintain a desired voltage. In addition to voltage measurements, the Volt/VAR object utilizes a power measurement at a link object to determine how to switch various capacitor objects on the system in and out of service. Due to differences in the timing of power calculations in the Forward-Back Sweep (FBS) and Newton-Raphson (NR) power flow solvers, capacitors may switch at slightly different intervals for the same system. The overall control behaves the same in both solver methods, but this difference in capacitor timing may result in different final operating points.

Fig. 9 shows that bus voltages are low and the reactive power is plotted as a baseline comparison for the controlled responses.

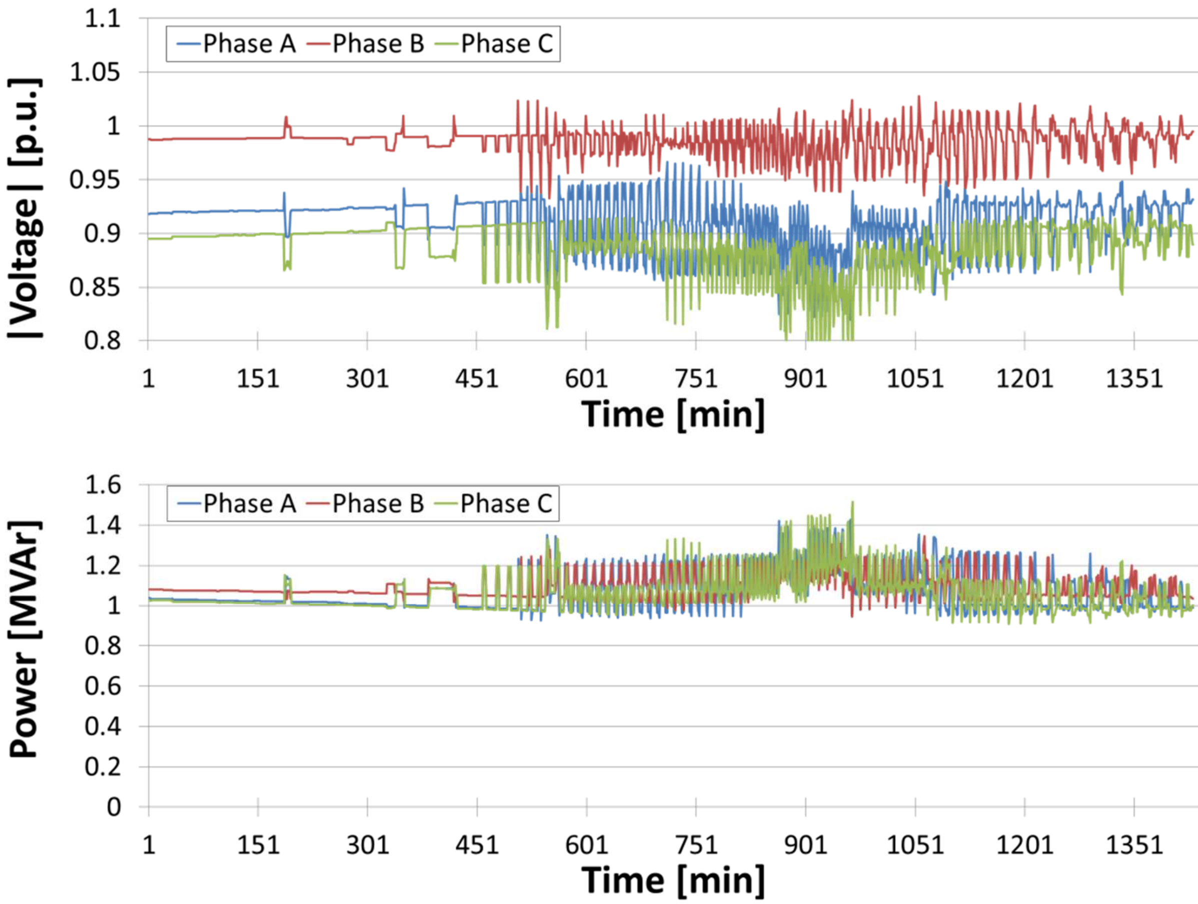

Fig. 9 IEEE 13 distribution system without Volt/VAR Control

In this case, Conservation Voltage Reduction (CVR) is used on all of the cases without reactive support and energy, in addition to the other previously seen cases, and the effects upon losses and owner factor correction are observed. In previous cases, voltage was monitored at a primary side node on the most heavily loaded section of the feeder. This voltage was then regulated to the nominal voltage (7200 V). Before applying CVR to the system, voltages were monitored throughout the system. It was found that the heavy loading on the system was already driving voltages near the lower ANSCII limit of 114 V on 23 heavily loaded areas, while rising to near the maximum of 126 V near lesser loaded areas. However, as a hypothetical example, a voltage reduction of 100 V was applied at the 7200 V monitored node (an approximate 1.5 volt reduction on the 120 V consumer side), so that effects could be observed. The bus voltages are raised after the taps on the regulators are adjusted and additional capacitors are activated. The reactive power demand at the feeder is considerably lower due to the local production of reactive power at the distribution level. Fig. 10 shows bus voltages and the reactive power is plotted as a baseline comparison for the controlled responses with Volt/VAR Control

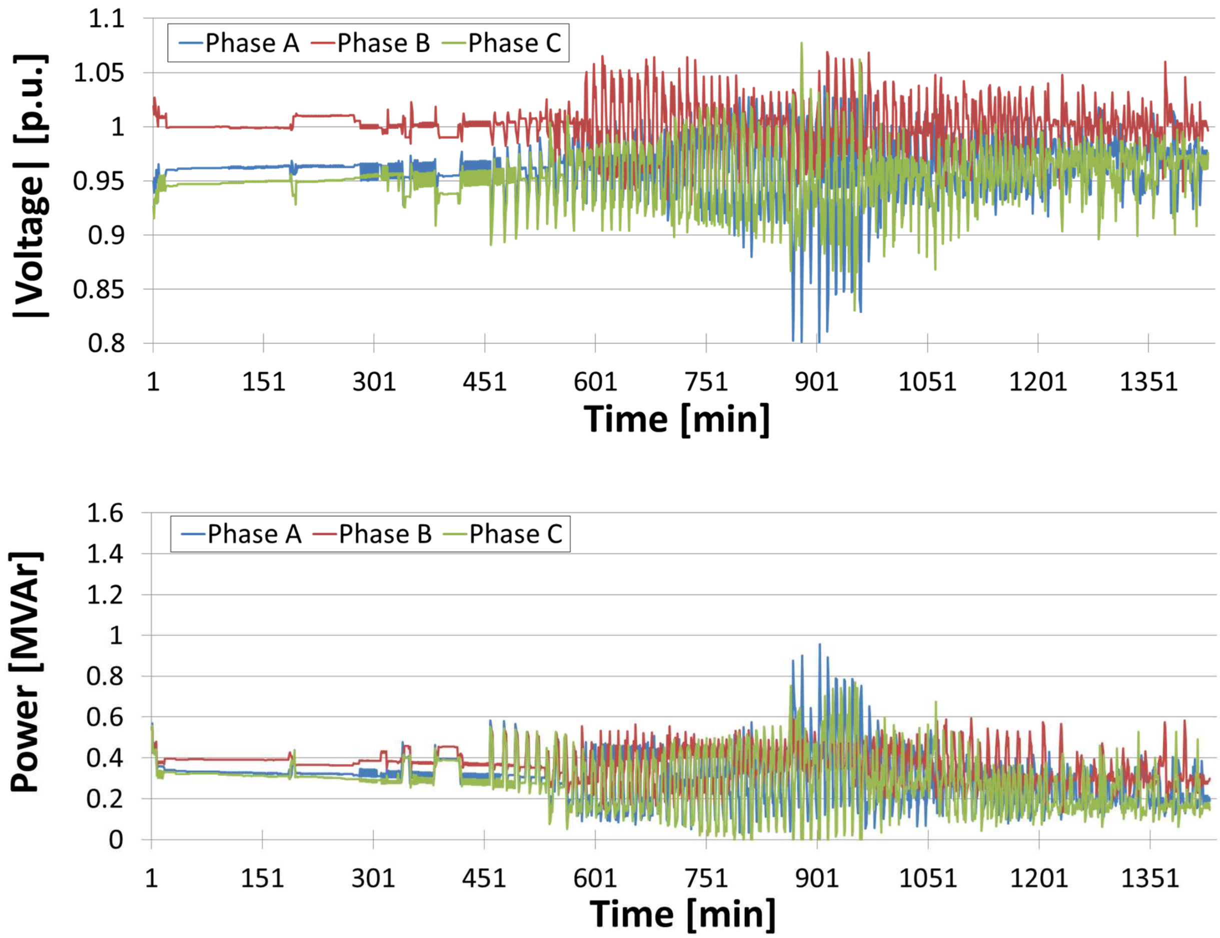

Fig. 10 IEEE 13 distribution system with Volt/VAR Control