A Model-Based Design of Cyber-Physical Energy Systems

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Abstract— ***Cyber-Physical Energy Systems*** **(CPES) are an amalgamation of both power gird technology, and the intelligent communication and co-ordination between the supply and the demand side through distributed embedded computing. Through this combination, CPES are intended to deliver power efficiently, reliably, and economically. The design and development work needed to either implement a new power grid network or upgrade a traditional power grid to a CPES-compliant one is both challenging and time consuming due to the heterogeneous nature of the associated components/subsystems. The** ***Model Based Design*** **(MBD) methodology has been widely seen as a promising solution to address the associated design challenges of creating a CPES. In this paper, we demonstrate a MBD method and its associated tool for the purpose of designing and validating various control algorithms for a residential microgrid. Our presented co-simulation engine GridMat is a MATLAB/Simulink toolbox; the purpose of it is to co-simulate the power systems modeled in GridLAB-D as well as the control algorithms that are modeled in Simulink. We have presented various use cases to demonstrate how different levels of control algorithms may be developed, simulated, debugged, and analyzed by using our GridMat toolbox for a residential microgrid.**

I. INTRODUCTION AND RELATED WORK

Currently in the power systems industry, there is a paradigm shift from the traditional, non-interactive, manually-controlled, power grid to the tight integration of both cyber information (computation, communications, and control - discrete dynamics) and proper physical representations (the flow of electricity governed by the laws of physics - continuous dynamics) at all scales and levels of the power grid network. This new grid which features this cyber and physical combination is termed as *Cyber-Physical Energy Systems* (CPES) [1], and it is expected to improve the reliability, flexibility, efficiency, cost-effectiveness, and security of the future electric grid [2, 3]. However, the introduction of *Distributed Energy Resources* (DERs) including renewable sources, and new types of loads (specifically *Electric Vehicles* (EVs)) in the residential distribution grid presents the challenge of multi-level monitoring and control for supply and demand management to an already complex and heterogeneous grid. A consequence of the rapid addition of these DERs would be that traditional power system design methodologies become more time-consuming to perform and that the ability to preempt grid problems would be more difficult. Authors in [4] demonstrate a potential model of future energy systems: a cyber-physical network which consists of many diverse energy components, each of which is equipped with a local embedded system. Developing an optimal grid is a complex task, due in part to the need for modeling and analyzing the system at both different scales and across different information domains. To solve this issue, *Model-Based Design* (MBD), which has been proposed in recent publications [4, 5, 6], allows for modeling both the physical and cyber components concurrently. Moreover, it allows cyber-physical co-simulation to explore for various design alternatives required for designing, validating, and testing. With such an implementation, power systems may be virtually analyzed and advanced control algorithms may be developed without the need for physical prototypes because software would be able to estimate the dynamic behavior of the system under a large variety of conditions.

In [5], a generic MBD methodology for a cyber-physical system design has been discussed. In [4], a novel cyber-based dynamic model is proposed where the mathematical model is primarily based on the cyber world which is helpful for distribution decision making. While various domain-specific power system simulation tools currently exist, there is a critical gap of advanced system-level design methodology and tools in the modeling and simulating (of both discrete and continuous dynamics) of the cyber and physicals portions of CPES concurrently. State-of-the-art domain-specific power system modeling tools lack the capability to capture the cyber-components of CPES during modeling and simulation. On the other hand, tools capable of describing the discrete event dynamics of the cyber components are not well equipped with the models needed to best represent the physical dynamics of power systems. Therefore, cyber-physical co-simulation of different domain specific tools has been seen as the possible enabling technology [7, 8, 9].

In [6], a MBD framework that uses SystemC for the purpose of designing embedded systems for energy management is proposed. A residential electrical energy simulation platform (HomeSim) is proposed in [10] to evaluate the impact of technologies such as renewable energy and improved battery storage through centralized and distributed energy managements as well as smart appliances. A co-simulation tool MATLAB & EnergyPlus [11] for building energy automation solution (MLE+) is proposed in [7]. In [9], a Ptolemy II-based [8] co-simulation software environment, *Building Controls Virtual Test Bed* (BCVTB), for coupling different simulation programs is presented (co-simulation including EnergyPlus [11] and Matlab). In [12], a co-simulation of GridLAB-D [13] and MATLAB is used to model integrated renewable energy and

Demand Response[1] (DR). In this co-simulation, the control developed in MATLAB (which acts as slave of the simulation) is executed as a co-process of GridLAB-D and cannot support a debugging utility function for the control engineers. To achieve cyber-physical co-simulation capability and to enhance the physical library of GridLAB-D, in [14], authors have presented a technique of using a functional mockup interface to integrate Modelica-based components with GridLAB-D. In [15], a co-simulation platform that consists of communication and power systems (ns-3 [16] and GridLAB-D) is presented.

CPES covers various scales and levels including residential/commercial/industrial buildings [17, 18], microgrid (see Section III for details), distribution (substation and feeder levels) and transmission levels [19], and generation side [20]. In this paper, we consider a residential microgrid as an example of a CPES and demonstrate the capability of the MBD methodology. Moreover, we present our cyber-physical co-simulation tool GridMat (see Section IV.C) for the purpose of residential microgrid modeling and simulation.

The rest of the paper is organized as follows. Section II presents the itemized content of the paper. After describing the residential microgrid in Section III, we present the MBD of the residential microgrid in Section IV. Experimental results are discussed in Section V before concluding the paper in Section VI.

II. Content of This Paper

- We present a model-based design methodology for a residential microgrid which is an example of a CPES. We also present a MATLAB/Simulink toolbox (GridMat) where structural and behavioral aspects of a residential microgrid may be modeled using GridLAB-D from the *Graphical User Interface* (GUI) of the GridMat tool, and various control algorithms may be modeled using the graphical language of the Simulink. Moreover, using this GridMat tool, the developed cyber-physical model may be simulated, debugged, and analyzed.
- In the MBD methodology, MATLAB/Simulink utilities such as the embedded code generator are used for implementable software generation in order to support a high fidelity *Hardware-In-Loop Simulation* (HILS).
- To demonstrate the capability of the presented MBD methodology for a residential microgrid, we have modeled a large residential microgrid (using IEEE 13 node test feeder and 1000 houses with various appliances, etc.) and have studied various use cases of developing control algorithms that would be able to address some of the challenges that might occur in a residential microgrid such as demand response, peak load reduction, and reliability (voltage drop control at the demand side).

III. Residential Microgrid

The traditional power grid where electricity typically flows only from large scale generation sites (mostly fossil-fuel-powered and nuclear powered) to a distribution grid through the transmission lines has been transformed to a more (bi-/)multi-directional electricity flow system due to integration of various DER including renewable sources. This shift in electricity flow, rising costs of electricity production, and a better understanding of environmental impacts require balancing mechanisms between the supply and the demand of electricity [21]. As a solution to this challenge, microgrid solutions have been proposed both in academia and industry. A microgrid is a localized and semi-autonomous group of electrical energy resources (which consists of different storage and generator technologies such as photovoltaics, wind turbines, fuel cells, and microturbines) and electrical loads (industrial, commercial, and residential consumers) that connects to the traditional power grid (macrogrid) [21]. A microgrid can operate in two modes: (1) grid-connected mode where the microgrid is connected directly to the macrogrid, and (2) island mode where the microgrid can disconnect itself from the macrogrid so as to operate autonomously in physical and economic conditions. This capability to operate in these modes allows a microgrid to provide additional reliability to the demand side.

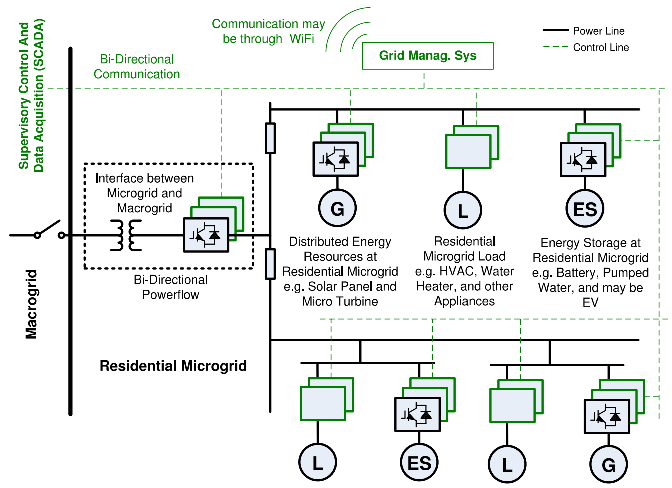


Fig. 1. A conceptual view of a residential microgrid

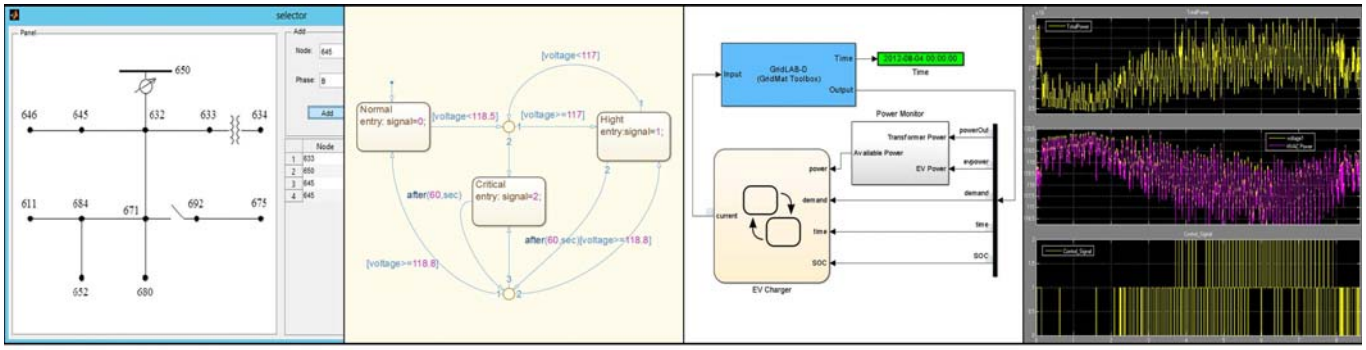
Besides typical deployment of microgrid in military installations, universities, and remote locations, a microgrid may be deployed in a typical residential area[2]. Fig. 1 illustrates a high level overview of a residential microgrid which consists of residential loads as well as DERs such as an energy storage.

Safety, security, protection, demand-side energy management, power quality, imbalance/asymmetry, plug and play operation of DER systems, distributed voltage/frequency profile control, and non-autonomous/autonomous operation are some of the challenges in designing and operating a microgrid in the residential area [22]. To solve these challenges, various local distributed controllers will need to be designed typically at the distribution level.

The design and validation of such a residential microgrid is a complex and demanding task because of the heterogeneous multi-domain components of the system. MBD method enables the designers to develop and validate the CPES by abstracting the details of a large system at a high level so as to perform the needed design space exploration in a short time; moreover, it is useful to validate and evaluate the design quickly without using real physical plant.

[1] Demand response in power grids is a dynamic demand mechanism to manage customer power consumption in response to supply conditions due to the balancing of supply and demand of power.

[2] In the case study of this paper, we have considered a microgrid that is deployed in a residential area, and name it as a residential microgrid.



a) Modeling the Power Grid b) Modeling the Grid Management Algorithms c) Cyber-Physical Co-simulation in GridMat d) Verification and Validation

Fig. 2. Using GridMat tool for MBD of the residential microgrid

IV. Model-Based Design

In the scope of the presented MBD methodology, we develop a *model-in-the-loop simulation* (MILS) environment using multi-tool co-simulation capabilities. Our methodology is capable of generating control software which will allow us to validate our model and increase the fidelity of the simulation by using both *Software-In-the-Loop Simulation* (SILS) and HILS environments.

Before starting to model a residential microgrid, the requirements, components/subsystems, structure, location, and problems should be defined. For example, we want to design a residential microgrid which consists of 1000 single family houses with multiple instances of level II EV chargers and low-rate step-down transformers in a mid-size distribution power grid. This residential microgrid should be able to manage and orchestrate the operation of all the individual chargers and transformers with respect to EV charging, demand response, and reliability of power system using residential load control. By using this information, the CPES could be modeled, simulated, and validated according to the MBD methodology. Fig. 2 shows the main steps of the MBD methodology of a residential microgrid. We explain these steps in detail as follow:

A. Modeling the Power Grid for the Residential Microgrid

To develop and analyze a CPES, the model of the physical plant which consists of both the structural and the behavioral models should be developed according to the requirements. The structural model of a residential microgrid includes the building-architectural model of houses, end-use appliances, distributed energy resources, transformers, and distribution power grid. On the other hand, the dynamic parts of a residential microgrid such as the appliance tasks, energy demand, weather, etc. are captured by behavioral modeling.

GridLAB-D is the most promising state-of-the-art tool for modeling a distribution power grid, especially a residential microgrid. GridLAB-D is an open-source, agent-based, multi-domain (power domain, market domain, weather domain, and built-environment domain such as building-related structural parameters) modeling and simulation tool for distribution power systems which is developed by PNNL [13]. *Discrete Event* (DE) model of computation, and agent-based simulation enable GridLAB-D to model and simulate a large scale distribution power grid at different levels of granularity which allows for the modeling of the end-use appliances necessary for a residential microgrid. However, GridLAB-D is limited at modeling and designing the discrete dynamics required for the microgrid management, e.g., the embedded systems and the control algorithms in CPES.

B. Modeling the Grid Management Algorithms

We have used Simulink the data flow graphical programming language tool to design, model, and simulate various controllers for a residential microgrid. MATLAB/Simulink has a rich library to implement various types of control algorithms, e.g. *Model Predictive Control* (MPC).

C. Cyber-Physical Co-Simulation

After modeling both the continuous and discrete dynamics of the residential microgrid, the integrated model needs to be simulated on a desktop-based simulator to analyze, verify, and validate according to design requirements. By adjusting the parameters of the model, different behaviors of the model may be captured through cyber-physical co-simulation which allows designers to validate the design precisely. For a residential microgrid, we have developed GridMat [23] which is a multi-tool/multi-domain co-simulation platform to overcome the limitation of modeling and simulation of a cyber-physical distribution power system.

GridMat: is a cyber-physical MATLAB toolbox that supports modeling, simulation, analysis, and validation of a distribution power system such as a residential microgrid. The major features of GridMat are: (1) access to all MATLAB toolboxes as well as the Simulink graphical programming language to design, develop, and debug advanced, hierarchical, and distributed control algorithms. Therefore, device-level and various *Supervisory Control And Data Acquisition* (SCADA)-level control algorithms may be developed for the residential microgrid very effectively; (2) a user friendly GUI for the state-of-the-art GridLAB-D tool; (3) a model creator that helps designers create the structural and behavioral models of a residential microgrid; (4) a data analysis utility that enables the designers to analyze the simulation results and the grid impact under various scenarios and allows modification of the controllers; (5) an embedded C code generator allows the designer to conduct a HILS for the purpose of validating the fidelity of the design.

In GridMat, GridLAB-D and MATLAB/Simulink communicate together through the HTTP protocol over the TCP/IP stack. A HTTP client wrapper is developed in GridMat in order to handle the co-simulation data exchange through HTTP between GridLAB-D and MATLAB/Simulink. Fig. 3 illustrates

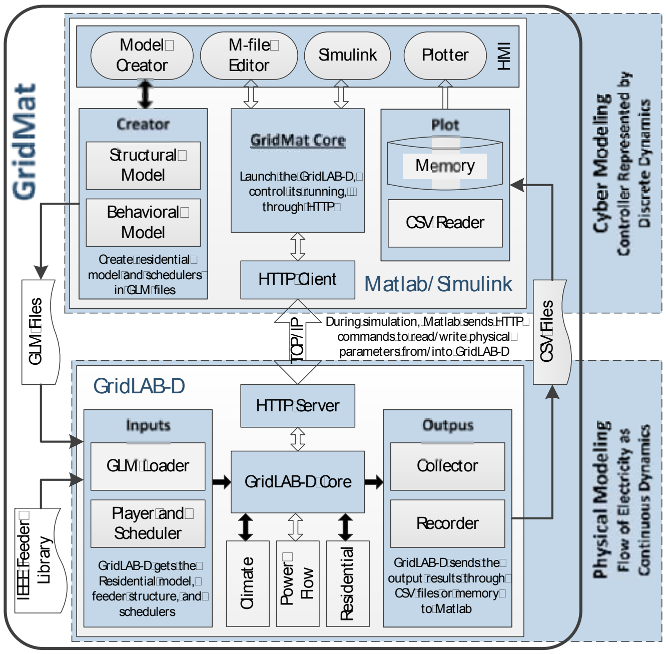


Fig. 3. Our GridMat architecture

the structure of GridMat in detail. The GridMat core is the master of the co-simulation that runs an instance of GridLAB-D, makes a TCP/IP connection to the GridLAB-D instance, controls the co-simulation run time, and coordinates the writing and reading of parameters from and to GridLAB-D. Also, the core runs controllers which are implemented in the m-file editor or Simulink. The creator block in MATLAB creates GLM files (the GridLAB-D model files) based on the structural and behavior models which the user defines through the *Human-Machine Interface* (HMI). The GridLAB-D core loads the input GLM files and the IEEE test feeder library to simulate the physical plant of the microgrid by using different modules such as climate, power flow, and residential. It also generates some output files (CSV files) which may be used by the GridMat plotter in MATLAB to show simulation results to the user for validation and verification purposes.

D. Verification and Validation

The behavior of the control algorithms may be captured by formal verification and validation. In this step, the simulation result is analyzed and verified to ensure that the design requirements have been satisfied. An iterative approach may be applied here for debugging and validating the design by revisiting previous steps to modify the models of the physical plant, embedded computational system, control algorithm, and parameters of the models. The embedded software part may be tested without the real physical plant by using the HILS capabilities of GridMat. In HILS, a hardware platform should be selected to interact with the physical plant and run the control algorithm while it is able to persist in the environment. Then, the modeled controllers should be synthesized to generate an embedded software that may be executed on the real hardware. To perform HILS, the physical plant runs on the simulation tool (GridLAB-D) while the controller runs on the real embedded hardware and communicates with the simulated physical plant through our GridMat.

TABLE I
HOUSE AND APPLIANCE SPECIFICATIONS

Object	Type 1	Type 2
Number of stories	1	2
Floor area	2100 sq.ft	2500 sq.ft
Heating system	GAS	GAS
Cooling system	Electric	Electric
Thermal integrity	NORMAL	ABOVE
Motor efficiency	AVERAGE	AVERAGE
Number of occupants	3	5
Heating set point	68° F	68° F
Cooling set point	72° F	72° F
Light power	1.2 kW	1.5 kW
Dishwasher power	1 kW	1.5 kW
Water tank volume	40 gal	50 gal
Water heater power	3 kW	4 kW
Clothes washer power	0.8 kW	1 kW
Miscellaneous	0.7 kW	0.8 kW
Compressor power	0.5 kW	0.6 kW
Oven	2.4 kW	3 kW
Oven set point	500° F	500° F
Dryer power	2 kW	3 kW

V. CASE STUDY EVALUATION

We demonstrate our tool and methodology using various use cases of a residential microgrid. The detailed residential microgrid model is present in [24]. In this model, 1000 residential single family houses are randomly distributed in the IEEE 13 node test feeder [25]. Each step-down transformer is connected to a node of the IEEE 13 node test feeder, and hosts a range of 3 to 7 houses. These step-down transformers range in rating from $15KVA$ to $35KVA$, depending on the number of connected houses. The houses are randomly selected from two types of houses (Type1 and Type2) which have a variety of end-use appliances such as dishwasher, lights, water heater, plug load (miscellaneous), refrigerator, clothes washer, dryer, and oven. Table I describes the specifications of our model.

We have chosen Newark, NJ, USA as the location for our residential microgrid and have simulated the model for both Summer and Winter seasons. All the structural and behavioral modeling of the power system (the physical plant) has been performed through our developed GridMat tool. Fig.4 illustrates the total average power consumption of a typical Summer and Winter day for two types of houses in our developed residential microgrid model. We have validated the fidelity of our model and the simulation results of various end-use loads and/or appliances as well as the average total power consumption of the houses with different sources [24, 26].

As we discussed in section III, demand response for peak-load reduction, power quality, and voltage drop control are some of the challenges for current residential microgrids. We propose implementing distributed control mechanisms where the controls of such are developed by the MBD methodology in GridMat by using different MATLAB/Simulink toolboxes such as MPC and Stateflow.

A. Residential Collaborative EV Charging

Higher rates of EV penetration will have a negative impact on the electrical power grid because uncoordinated EV charging on a mass scale at the secondary distribution grid would negatively affect both the total load and peak load power [27]. The results in [27] show that 30% of peak load power usage can be attributed to EV charging in the distribution grid. To address this negative effect, one solution could be to upgrade the power

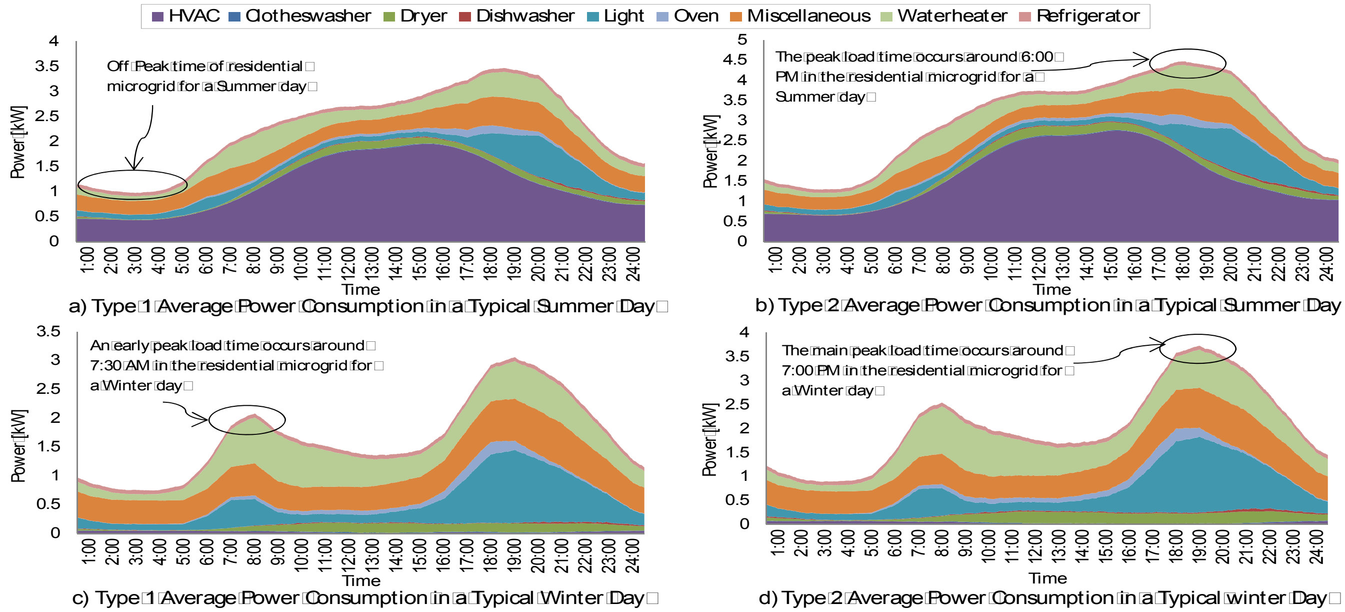


Fig. 4. Average power consumption of a house in our residential microgrid

system infrastructure by changing the transformers and adding more power plants to provide more energy to the residential grid [28, 29]. Unfortunately, this solution would undermine the economic and environmental benefits of EVs. Another solution, which would not have such a drastic downside, could be to control and coordinate the EV charging locally or at the substation level to mitigate the impact of EV charging from generating a peak [30]. In order to implement this solution and to balance the supply and demand, we need new control algorithms which may be tested, verified, and validated through MILS. Our presented MBD method and the GridMat tool may help in exploring the possible alternatives.

We have demonstrated the "fair-demand" control algorithm to coordinate the EV charging by adjusting the charging current of each EV according to its demand and the available power at the transformer level. EV demand is defined by the expected amount of energy that the EV needs to drive for the next trip divided by the duration that the EV stays connected to the charger. Equation 1 shows the demand definition in which D_i, E_i, and t_i are the demand, the expected needed energy for the next trip, and the time to leave for the next trip, respectively.

$$D_i = E_i / t_i \qquad (1)$$

The "fair-demand" algorithm uses weights based on the demand parameters to adjust the charging current. According to Equation 2, W_i is the weighted demand for an EV.

$$W_i = \frac{D_i}{\sum D_j} \qquad (2)$$

We have assumed that the level II EV chargers with the maximum rate of $7.2 KWh$ are used in the residential microgrid model. Since the level II EV charger works at $240V$, the maximum current for charging, per Ohm's Law, is $30A$. Equation 3 shows the C (current of charging) according to the weighted demand. P is the available power at the transformer level.

$$C_i = Min(30, \frac{W_i * P}{240}) \qquad (3)$$

The "fair-demand" algorithm will equally share the rest of the available power to charge the battery full after all EVs receive their demanded energy. Fig. 5 illustrates the state machine of the "fair-demand" algorithm implemented in Simulink.

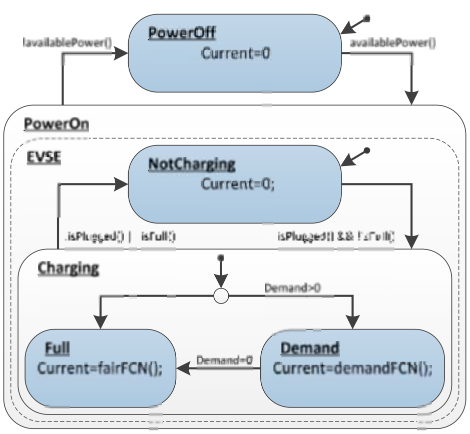


Fig. 5. Stateflow model of the "fair-demand" EV charging algorithm

We have modeled the behavioral aspects of the EV and the *Electric Vehicle Supply Equipment* (EVSE)[3] as per [24] where EV follows Gaussian distributions for the arrival and the departure time. The mean time of arriving and leaving are 5:30 PM and 7:30AM, respectively. The EVSE controls the charging current and receives some information from the EV such as the time to leave, the expected next trip energy demand, and the specifications of the EV. Besides the "fair-demand" control algorithm, we also demonstrate how to develop the "fair-shared" control algorithm [32] that may equally divide the available power among all the EVs connected to one transformer in our GridMat tool. Moreover, we implement a EV charging control policy that supports "deferral-based" EV charging (load-

[3] Our proposed model and algorithm are for advanced EVSEs which are able to provide variable rate current supply (multiple amperage adjustment capability) on-demand [31]

shifting) where all householders defer the EVs charging to 9:00PM due to cost of electricity and peak load time of residential microgrid. In this mode, all EVs are charged at a rate of 3.2KWh to prevent the transformer from overloading. These control algorithms were experimented on, and the simulation results of them are shown in Fig. 6.

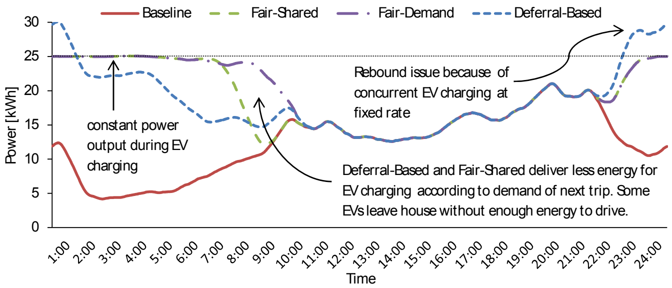


Fig. 6. EV charging simulation result at transformer level

While analyzing for a suitable control algorithm, we see that the result of the "deferral-based" algorithm shows a rebound effect due to all the EVs starting to charge after 9:00PM. However, the "fair-shared" and the "fair-demand" do not show such a rebound effect and actually keeps the power output of the transformer at its nominal rate (25KW with 5 connected houses). In general, the "fair-demand" delivers more energy to the EV compared to the "fair-shared" and the "deferral-based" control algorithms, because the "fair-demand" algorithm charges EVs according to their demand and tries to deliver all necessary energy to all the EVs before they leave the houses. However, in the "deferral-based" and the "fair-shared" algorithms all EVs receive equal energy, though at the cost of some of the EVs leaving their houses without sufficient energy to complete the expected trip. Such analysis at a high abstraction level in the MBD allows for development of control algorithms in a rapid and efficient manner, while also assessing the benefits and consequences of implementing them.

B. Residential Demand Response

DR mechanisms try to reduce the customer power consumption during peak load times or in response to market prices. Since the majority of energy demand, which accounts for 38% of the total energy usage, comes from residential buildings due to a large portion (on average 33%) being used in *Heating, Ventilation and Air Conditioning* (HVAC) systems, it is an attractive target for demand side energy management, especially during the peak load time period [33, 34]. Also, the water heater is another flexible load in most homes which significantly helps to reduce household power consumption during peak load time. Given that peak load time is generally a critical time period in the energy market, many utilities have a vested interest in encouraging their consumers to optimize their power consumption. If the demand side consumption could be appropriately curtailed, utilities would not need to add more power plants to compensate for the extra demand of energy. Some examples of demand control policies that some utilities might implement include *Time-Of-Use* (TOU) rate and *Direct Load Control* (DLC) [35] to encourage customers to reduce their demand during the peak load time. In DLC, customers make a contract with utilities, granting them the ability to control some of their appliances during the peak load time in return for some savings on their electricity bills [35]. Examples of DLC that utilities commonly use include reducing the heating set point of the water heater and/or increasing the cooling set point of the HVAC system based on the weather. We have used MPC to control power consumption of the houses (see Fig. 7) according to a DLC signal while the inside temperature and water temperature are within the ANSI/ASHRAE specified [36] comfort zone[4].

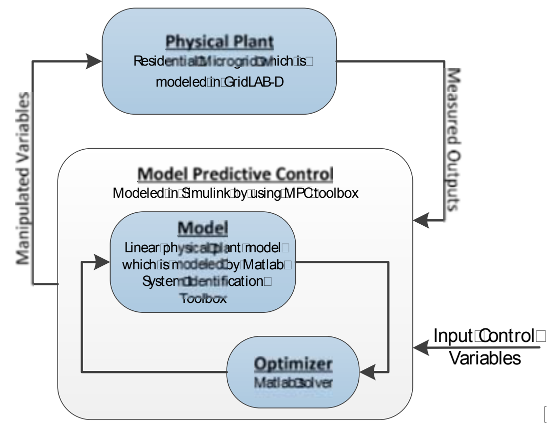


Fig. 7. Model-based design of MPC in residential microgrid

Equation 4 shows the cost function of the MPC controller that we used to control the power consumption of a house during DLC. P_{pred}, P_{ref}, u_i, and u_{ref} are predicted power output, desired power output, manipulated variable, and optimal resting value, respectively. In this cost function, w is the weight for each of the variables.

$$I = w_1 (P_{pred} - P_{ref})^2 + \sum_{MV} w_{2i} (\Delta u_i)^2 + \sum_{MV} w_{3i} (u_i - u_{rest})^2 \quad (4)$$

In such a DR scenario, the utility sends a *Demand Response Signal* (DRS) to the *Home Energy Manager* (HEM) which changes the cooling and heating set points of the HVAC and the water heater, respectively. During the experiment, the DRS is sent between 4:00 PM to 8:00 PM to reduce the power consumption to 3KW. We have validated the model for two different algorithms, MPC and DLC. In both the algorithms the cooling and heating set points change between $70^\circ F$ - $78^\circ F$ and $115^\circ F$ - $130^\circ F$ (comfort zone). In the DLC algorithm, the HEM increases the cooling set point to a maximum value of $78^\circ F$ and decreases the heating set point to a minimum value of $115^\circ F$ when the DRS is issued. However, these manipulated variables are changed by MPC according to a future prediction of the power output, weather, etc. Fig. 8 shows the results of MPC and DLC as well as the baseline which has no controller.

Our MBD methodology allows us to quickly validate various control algorithms for implementing a DR program by the utilities. During validation, we have observed that MPC reduces the power consumption to 3KW when DRS is generated; however, DLC is not able to keep power consumption at 3KW in this period. Moreover, DLC shows rebound effect after the DRS because of decreasing cooling set point and increasing heating set point.

[4] Comfort zone is defined as a term of the *predicted mean vote* (PMV) which is a function of the average temperature of the air surrounding the occupant, air speed, humidity, time, location, human activity, expected human clothing, etc.

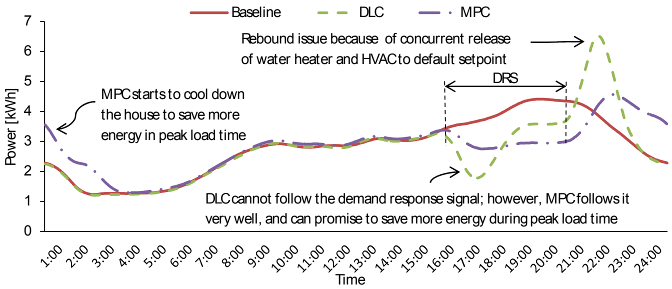


Fig. 8. Average power consumption of a house using demand response signal

C. Grid Reliability

Controlling the voltage drop seen at the extremities is one of the challenges in designing and developing a reliable residential microgrid. One of the ancillary services[5] in the power system is to maintain the voltage level at a particular range to maintain reliable operations of the power grid and prevent adverse effects on the operations of equipment. Typically ancillary services are provided by the generation side; however, recent researches show that ancillary services may be provided through demand side energy management in a residential microgrid [37]. The voltage is not constant through the power system because the conductors and power system components exhibit an impedance to the flow of current and the voltage tends to decrease as we move closer to the load. Therefore, voltage drop may be represented as:

$$\Delta V_{drop} = I_{load} \times Z_{cond} \tag{5}$$

The power consumption of a load, and the impedance of conductors may be represented as:

$$P_{load} = I_{load}^2 \times Z_{load} \tag{6}$$

$$Z_{cond} = Z_{line} + Z_{trans} \tag{7}$$

In Equation 7, Z_{line} and Z_{trans} are the transmission line and transformer impedance. Finally, voltage drop is represented in Equation 8. This equation shows how power consumption, load impedance, line impedance, and transformer impedance impact the voltage drop.

$$\Delta V_{drop} = \sqrt{\frac{P_{load}}{Z_{load}}} \times (Z_{line} + Z_{trans}) \tag{8}$$

In a typical power grid, the voltage drop can be controlled by using voltage regulators and transformer taps. However, in microgrid, these solutions are not very effective because the output voltage of the renewable distributed energy resources such as a solar photovoltaic may be reduced by cloudy weather [37]. In the scope of this paper, we demonstrate through our GridMat tool how to develop an algorithm to reduce the voltage drop for a residential microgrid by reducing demand during lower system voltage. In this case, we have used smart appliances to control local voltage drop by reducing its power consumption. A dryer consists of a coil to heat up the dryer and a motor to turn the drum. Since the coil of dryer consumes a large amount of power and that most consumers usually do not care (excessively) about the duration it takes to complete a drying task, we have developed a control algorithm to reduce the voltage drop by operating the dryer in an energy saving mode.

[5] Ancillary services support the reliable operation of the transmission of power from generations to retail customers. Ancillary services include scheduling/dispatch, voltage/frequency control, load following, system protection, and energy imbalance.

We have defined three modes of operation for a dryer: (1) normal; (2) high; and (3) critical. In normal mode, the dryer works with full capacity of its coil. The dryer reduces the coil capacity to 70% during high mode and turns off the coil in a critical mode. The motor of the dryer works normally during all of the above mentioned operation modes. The users can switch from the high or critical modes to the normal mode if they want to speed up the drying task at any time. The controller senses the local voltage and switches from normal to high mode when the voltage is less than 118V and from high to critical when the voltage is less than 116V. In reverse direction, we add a 0.4V dead band; therefore, it is 118.4V to switch from high to normal and 116.4V to switch from critical to high.

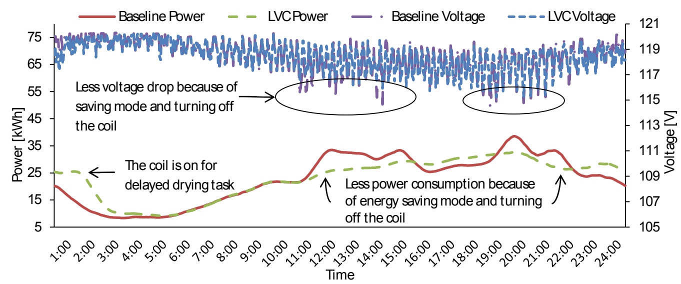


Fig. 9. Local voltage control by using smart dryer

Fig. 9 illustrates the results of the local voltage control that come from using a smart dryer. The *Local Voltage Control* (LVC) algorithm shows that there are smaller voltage drops compared to the baseline. LVC reduces the voltage drop by reducing the power consumption of the dryer when the voltage drop is high. The power consumption of the LVC algorithm is less than the baseline when the voltage goes below the thresholds. Our GridMat tool helps to quickly compare and validate different control algorithms to improve the power grid reliability before deployment into a real physical plant and the corresponding hardware.

D. Hardware-In-Loop-Simulation

After exploring the residential microgrid in MILS, we have generated the software as a C application by using MATLAB Embedded code generation for the purpose of running on real hardware. For this purpose, we have conducted a HILS by using GridMat and an open-source NETGEAR N300 wireless router which are both connected together through Ethernet. GridMat runs the model of the physical plant (residential microgrid) in GridLAB-D and handles the communication between controller and physical plant by using a HTTP wrapper. During HILS, GridLAB-D runs in real-time mode to emulate the physical plant. Fig. 10 shows the structure of the HILS which we have conducted to validate and test the controller on real hardware.

VI. CONCLUSIONS

In this paper, a model-based design methodology has been used to design, develop, and analyze a residential microgrid. Moreover, a cyber-physical co-simulation tool (GridMat) that has been developed by the authors for distributed power systems such as a residential microgrid is presented. Various use cases have been studied to demonstrate the capability of experimental MBD method for developing a heterogeneous multi-domain CPES. The results show that MBD is able to capture

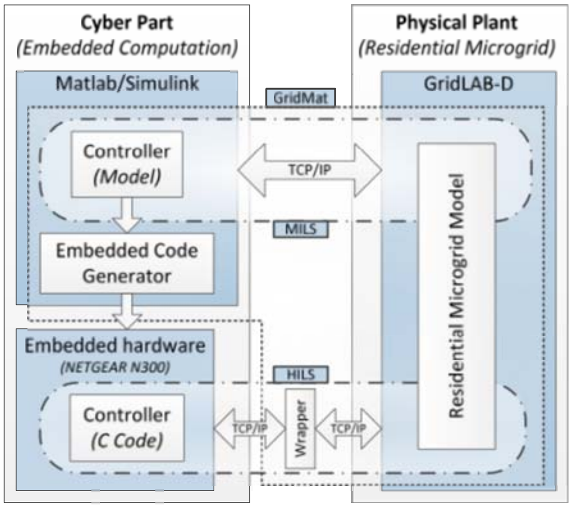


Fig. 10. Structure of MILS and HILS in GridMat

all aspects of CPES by modeling, simulating, and validating the design.

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