On Effectiveness of Smart Grid Applications using Co-simulation

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***Abstract*—The smart grid is a complex system that comprises components from both the power grid and communication networks. To understand the behavior of such a complex system, co-simulation is a viable tool to capture the interaction and the reciprocal effects between a communication network and a physical power grid. In this paper, we systematically review the existing efforts of co-simulation and design a framework to explore co-simulation scenarios. Using the demand response and energy price as examples of smart grid applications and operating the communication network under various conditions (e.g., normal operation, performance degrade, and security threats), we implement these scenarios and conduct a performance evaluation of smart grid applications by leveraging a co-simulation platform.**

I. Introduction

One of the goals of the smart grid is to provide efficient and reliable energy service to consumers by integrating modern communication technologies, renewable energy resources, etc. to the power grid [22]. Because the physical power grid and communication networks are essential components in the smart grid, it is critical to develop system-level modeling and simulation tools to study the interaction between the power grid and the communication network.

A single and unified co-simulation framework that integrates power grid and communication network is a viable tool for the research and development of the smart grid. As defined by Norling *et al.* [15], "*co-simulation is a methodology for simulating individual components concurrently of a larger system by different simulation tools which mutually exchange information in a collaborative manner*". Co-simulation will provide cost-effective means to evaluate and test smart grid technologies before deployment in the field [7], [20]. Broadly speaking, unlike independent simulators that treat the electric grid and the communication network as isolated environments, co-simulation can capture the interaction and the reciprocal effects between the communication network and the power grid in the smart grid [12], [17], [16], [14]. Particularly, co-simulation can be used to evaluate the impacts of the performance and security of communication networks on smart grid operations. In this way, we can determine communication system requirements to support smart grid applications and the behavior of these applications when the network is under various conditions raised by congestion, failure, and/or cyber attacks.

In this paper, we first review existing efforts on co-simulation for the smart grid. We then describe the power grid and communication network models and present a framework to explore scenarios for co-simulations. In our framework, we consider two orthogonal dimensions: one represents smart grid applications (e.g., demand response and market with dynamic pricing, etc.) and the other depicts operation conditions of the communication network (e.g., normal operation, network under attack such as false data injection and denial-of-service, and network quality-of-service degrade). Based on this framework, we then develop six scenarios. By using use the capabilities and features of the Fenix framework for Network Co-Simulation (FNCS), a High Performance Computing (HPC) simulation platform[1] [18], [3], we conduct co-simulations to evaluate the performance of smart grid applications for individual scenarios. Our data results show that the intertwined implementation of demand response and the dynamic energy market can effectively smooth power generation, maintain a balance between generation and demand, and reduce high peaks of power generation. All of these factors can consequently lower power losses and generation costs. In addition, Quality-of-Service (QoS) and security threats on communication networks are determining factors for the efficiency of smart grid applications.

The remainder of this paper is organized as follows: We review the state-of-the-art smart grid co-simulation in Section II. In Section III, we describe our simulation model and scenarios. In Section IV, we present a performance evaluation of the developed scenarios using the co-simulation platform. We conclude the paper in Section V.

II. Related Work

In this section, we conduct a literature review of the existing efforts on co-simulations for the smart grid. There have been a number of research efforts on building a co-simulation framework for the smart grid. Generally speaking, the existing work in this area can be classified into two categories [11]: (i) extension of one simulator to allow co-simulation, and (ii) integration of power grid simulator and communication network simulator into a unified co-simulation framework.

In the first category, existing research efforts such as [12], [13] developed co-simulation frameworks either by extending

[1]Certain commercial equipment, instruments, or materials are identified in this paper in order to specify the experimental procedure adequately. Such identification is not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

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power distribution features to enable the communication network or by integrating a power distribution system module within a communication network simulator. For example, Matlab/Simulink [12] uses a library named TrueTime [2], [5] to enable a communication network. Mets *et al.* [13] proposed a modular simulation environment to integrate a power distribution module within OMNET++. These co-simulation frameworks have the advantage of bypassing the hurdle of synchronization. Nonetheless, they are not scalable as they are confined to simulating simple scenarios. Simulation results could become unreliable, inaccurate, and unpredictable as the system grows in complexity and size [11].

In the second category, one challenge is to synchronize two completely different systems: a continuous time-based simulator (e.g., power grid) and a discrete event-based simulator (e.g., network simulator) [11]. A considerable number of research efforts have been conducted in developing co-simulation tools, which has the goal of integrating two independent simulators tools into a single and uniform simulation framework [6], [1], [8], [9], [10], [18], [3], [4]. For example, Hopkinson *et al.* [6] developed a framework, called the Electric Power and Communication Synchronizing Simulator (EPOCHS) that integrates simulator software: PSCAD/EMTDC for electromagnetic transient simulation, PSLF electromechanical transient simulation, and NS-2. In addition, PNNL (Pacific Northwest National Laboratory) developed the Fenix Framework for Network Co-Simulation (FNCS) for the smart grid [18], [3], [4]. Generally speaking, FNCS is a High Performance Computing (HPC) simulation platform, which integrates GridLABD [19], MATPOWER [21] (simulators for power distribution systems), and NS-3 [14] (a simulator for communication networks).

III. Co-Simulation Models and Scenarios

We use the FNCS developed by PNNL in our co-simulation study as it integrates GridLABD [19], MATPOWER [21], and NS-3 [14] and fits our needs to study interaction between cyber components and power grid applications. More details on the FNCS can be found in [18], [3], [4]. In the following, we first describe the power grid and communication network models that we developed in our co-simulation environment. We then present the scenarios used for our co-simulations.

A. Power Grid and Communication Network Models

As shown in Figure 1, our power grid comprises a substation and a residential load. The substation consists of a three-phase swing bus with a nominal voltage of 7200 V and a power rating of 4,500 kW (i.e., 1,500 kW per phase). A meter between the substation transformer and the load measures the total load and senses the energy demand, enabling the substation to adjust the power supply accordingly. As the energy supplier, the substation sets the maximum power capacity available in the energy market and sets the energy reference price based on the time of the day and the current energy demand. The residential load is made up of 300 houses connected to the power line through triplex meters. Each individual house is

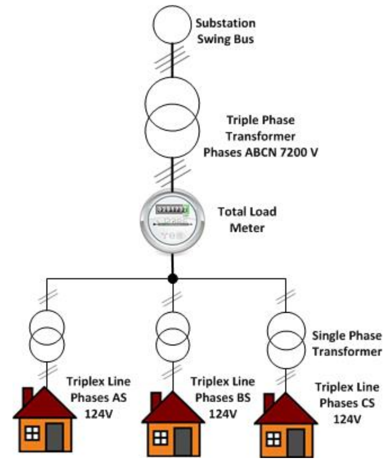


Fig. 1. Power Grid Simulation Model

equipped with a Heating, Ventilation, and Air Conditioning (HVAC) system with a controller.

As shown in Figure 2, our communication network consists of 300 nodes representing smart meters installed in individual houses. Smart meters are organized and grouped into clusters of 20 nodes forming local area networks. An edge network device in each cluster routes the data to a data aggregator point through a point-to-point communication link. The communication scheme is based on the UDP (User Datagram Protocol) transport protocol with a data rate of 4 Mbs and a transmission delay of 2 milliseconds for the point-to-point link, and a data rate of 10 Gbs and 3 milliseconds of transmission delay for local area networks. We choose UDP (User Datagram Protocol) because UDP as a connectionless protocol incurs a lower transmission delay in comparison with TCP (Transmission Control Protocol).

B. Co-Simulation Scenarios

To design the scenarios, we define two dimensions as illustrated in Figure 3. The first dimension shown on the x-axis represents different smart grid applications. Here, we consider two representative applications: demand/response and market/dynamic pricing. The second dimension shown on the y-axis represents operation conditions, including y_1: normal operation, y_2: network attacks that involve false data injection and denial-of-service, and y_3: network performance/quality of service. It is worth noting that our developed framework is generic and can be expanded to include other smart grid applications and networks in different states. In the following, we will detail these dimensions.

1) Smart Grid Applications: Through co-simulation, numerous smart grid applications that require a two-way communication infrastructure can be studied. In this paper, we consider two representative applications: demand/response and market/dynamic pricing.

Demand/Response: The goal here is to preserve a balance between power generation and load by adjusting energy demand dynamically. In the traditional power grid, customers

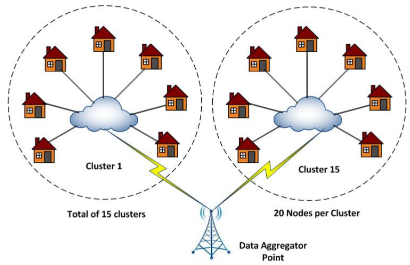


Fig. 2. Communication Network Model

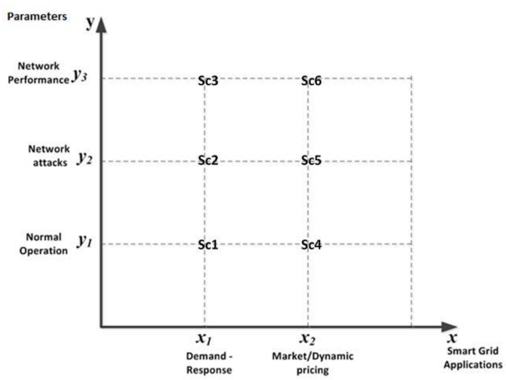


Fig. 3. Co-Simulation Space

cannot participate in the balancing process. Then, power generation was designed to address power imbalances and mitigate peak system conditions without taking end-users' dynamic load into consideration. Nonetheless, with smart grid technologies, end users that have the ability to adjust their energy uses become active participants in the process of balancing power generation and load.

Market/Dynamic pricing: Energy dynamic pricing is an effective to enable energy demand/response. In this approach, a control signal (e.g., a reference bid price) is sent to consumers, who can then adjust their energy use accordingly. The goal is to reach a win-win situation between sustaining the energy provider's profit with customer savings and enabling consumers to intelligently manage their energy consumption. There are three ways of doing pricing: Price based on Time of Use (ToU), Critical Peak Price (CPP), and Real Time Price (RTP).

2) Operation Conditions: In this dimension, we have the following operation conditions which will impact the system performance: (i) *Normal Operation:* This co-simulation environment represents optimal settings for the system, which maintain the grid operation in a faultless operational mode. (ii) *Network Performance:* Involves network settings such as data rate, throughput, and delay, which have an impact on the overall operation and performance of the grid. During co-simulation, we will tune these network characteristics and settings and evaluate their impact on smart grid applications (e.g., demand/response and energy market). (iii) *Security Threats:* Cyber attacks include false data injection and denial-of-service. Particularly, in a false data injection attack, an adversary exploits system vulnerabilities and manipulates data collected from the grid with a goal of disrupting system operations. As an example, an adversary can change the current bid price in the energy market and thus cause the energy clearing price to be unexpectedly higher at low peak hours or very low at peak hours. In the same way, an adversary can send false high energy demands to the substation, causing the substation to unnecessarily supply more energy than the current demand.

3) Co-Simulation Scenarios: We now describe our co-simulation scenarios. We will run different scenarios using smart grid co-simulation by combining the two orthogonal dimensions X and Y that were previously discussed. For example, scenario X_1Y_2 simulates demand response and load control applications under attack. The scenarios are listed as follows:

Scenario 1 - x_1y_1. Demand/Response: Normal Operation: In this scenario, co-simulation is set with an idea and optimal settings. The goal is to observe the grid in a faultless operation environment and verify: (i) the effectiveness of bidirectional communications and interactions between the power domain and the cyber domain; (ii) the effectiveness of demand/response and power balance in a faultless environment; and (iii) the smoothing of power generation and load adjustment during peak periods. To this end, we will compare the variation of total load with and without the demand/response feature enabled and collect output metrics, which include the total load and the statistics of HVAC systems.

Scenario 2 - x_1y_2. Demand/Response: Security Attacks: The goal of this scenario is to assess the overall performance and the effectiveness of the demand/response feature described in Scenario 1: X_1Y_1, but under security attacks. Then, we will not only inject false data into the system, but also create a denial-of-service through an overflow of network traffic. Under these conditions, we will observe system behavior and collect performance data.

Scenario 3 - x_1y_3. Demand/Response and Network Performance: This scenario aims to demonstrate the effectiveness of balancing power within the constraints of the communication network settings. This will allow us to evaluate the impact of network performance on demand/response applications. To validate this, we will set the data rate lower than the normal setting and increase the minimal transmission delay of the point-to-point link between the smart meters of the local network and the gateway.

Scenario 4 - x_2y_1. Energy Market and Normal Operation: This scenario will consist of evaluating economic benefits and the effectiveness of the double auction energy market and real time pricing in a faultless environment. The workflow of the energy market is shown in Figure 4 and can be described as follows: For every 5 minute period, energy suppliers bid the maximum power capacity and corresponding real time price that they can provide to the market. Simultaneously, end users bid the energy amount that they desire along with the price that they are willing to pay. When a period ends, the bidding

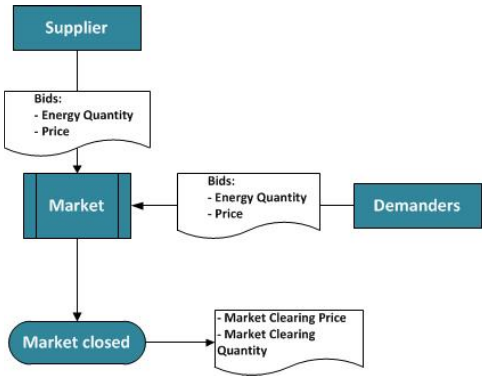


Fig. 4. Energy Market Work Flow

Object	Settings
Substation	- Nominal Voltage: 7200V - Power Rating: 4,500 KW (i.e. 1,500 KW per phase)
Residential Load	- 300 houses
Double Auction	- Maximum Bid Price (Price Cap): $3.78 - Maximum Capacity Bid Quantity: 1,100 KW - Initial price: $0.042676 - Real Time Price: Relative cost of power at a given time - Appliances in the Market: HVAC - Market Clearing: Every 5 minutes
Length of Simulation	1 day : 07-21 00:00 AM → 07-22 00:00 AM
Billing	- Hourly
Communication Network	- Nodes: 300 – Technology: Ethernet - Transport Protocol: UDP - Data Rate: 10 Mbps - Delay: 3 milliseconds

Fig. 5. Co-Simulation Settings

process stops. Then, the market clearing price and market clearing quantity are determined.

Scenario 5 - x_2y_2. Energy Market and Security Attacks: This scenario aims to demonstrate the effectiveness of energy market applications when under security attacks. By injecting false data and creating a denial-of-service, we will able to evaluate the impact on the network under an attack by considering the market clearing price, market clearing quantity, total energy used, and HVAC statistics.

Scenario 6 - x_2y_3. Energy Market and Network Performance: By tuning the network link data rate sufficiently low so as to create congestion, we will assess the effectiveness of the energy market and the impact of the network quality-of-service on the market in terms of market clearing price, market clearing quantity, and energy billing.

IV. Performance Evaluation

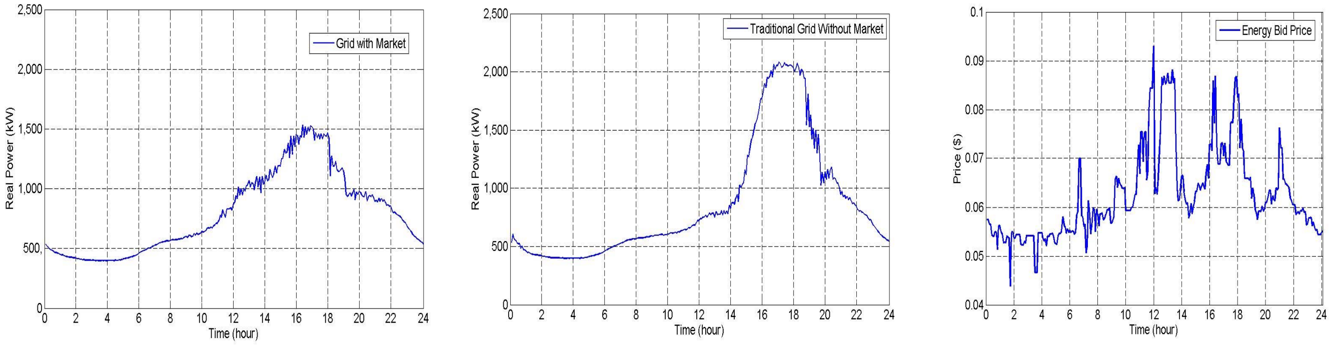
Our simulation was performed on an INTEL Core 3 workstation equipped with 8GB of DRAM. The installation of FNCS required a 64-bit Linux operating system and consists of prerequisite libraries (e.g., the ZeroMQ message library, the MPI library, and updated versions of gcc compilers), a Fenix module that encompasses the FNCS simulator API, a GridLABD simulator, and an NS3 simulator.

The settings for the co-simulation are shown in Figure 5 and outputs for co-simulations include: (i) *Total Load:* The aggregated load demand for the grid at a given time, (ii) *Market Clearing Price:* Energy price where demand equals supply; (iii) *Market Clearing Quantity:* The amount of energy sold when the market closes; and (iv) *HVAC Population Statistics:* The number of HVAC “ON" indicators at a given time. In the following, we present the results of our simulations. Note that the normal scenario represents the reference, showing the normal behavior of the grid in an idea environment and with optimal settings. To clearly visualize the impact of the individual scenario, we will show the result for both individual scenario and normal scenario. Because of there is no random in these simulation runs, error bars were not shown in all figures.

A. Demand Response

Normal Operation Mode: Figure 6 (a) and (b) represent the variation of the total load over 24 hours in the smart grid in the cases, where demand/response is enabled and not enabled, respectively. In the case where demand/response is enabled, the total load with demand/response is 1600 kW. In the case where demand/response is not enabled, the total load is 2290 kW. As we can see, for the same number of users and for the same energy demand, demand/response through market incitement can reduce the total power generation required to meet the demand and consequently reduce power losses. Effects of the market are more noticeable during peak periods. In the morning periods, where power demand is typically lower, the two curves are similar. From the afternoon to early evening, as the energy demand increases, the difference between the two curves is clearly visible. The total load in the grid system when demand/response is not enabled grows linearly until a peak condition occurs whereas we observe smooth variations on the system when demand/response is enabled. This is as expected because demand/response is capable of smoothing power generation and mitigating peak system conditions. Thus, these conditions contribute to reducing power generation costs and power losses. During a low peak, users increase their energy use as the power is affordable whereas users reduce their energy use at high peak times as the price is relatively high. Note that Figure 6 (c) shows the normal condition of reference bid price in 24 hours.

False Data Injection: High Capacity Bid (2500 kW) Figure 7(a) illustrates the variation of the total load over 24 hours for both normal capacity bid of 1100 kW and false capacity bid of 2500 kW, respectively. By injecting a false, large maximum capacity bid, there is more energy available in the market, causing the price to drop. As such, users can afford consuming more power even during peak periods without affecting their monthly bill. From 3 pm to 6 pm, a period of typically higher consumption, there is a total load increase of 588.612 kW. From 8 pm to 9 pm, a low peak period, the total load increases by 491.645 kW. Hence, to achieve a fair market and a win-win situation between energy providers and end users, the maximum capacity bid or the amount of energy the supplier provides to the market should be set optimally. On one hand, a small capacity bid will generate substantial profit for energy suppliers at a higher cost for the customers. On the other hand, an enormous maximum capacity bid will skyrocket energy

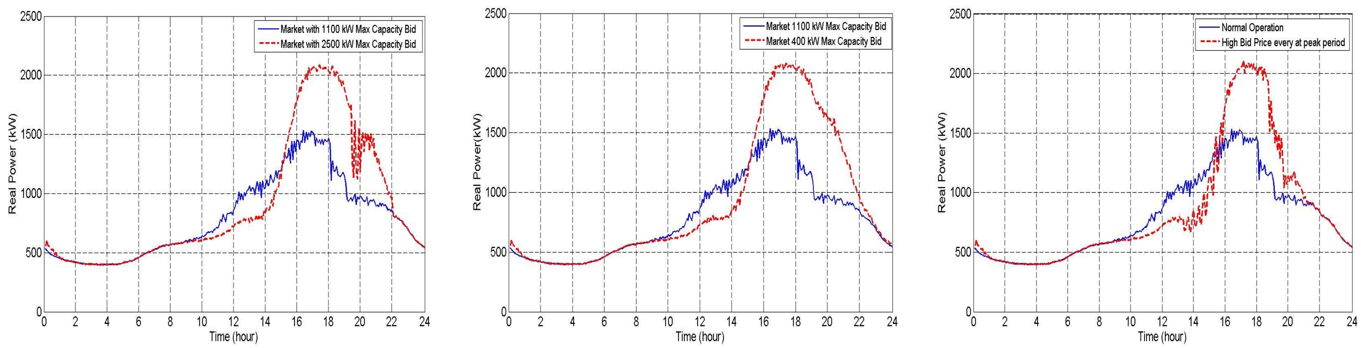


(a) Total Load with Market Enabled

(b) Total Load without Market

(c) Reference Bid Price in 24 Hours

Fig. 6. Normal Operation



(a) Capacity Bid at 2,500 kW

(b) Capacity Bid at 400 kW

(c) High Bid Price

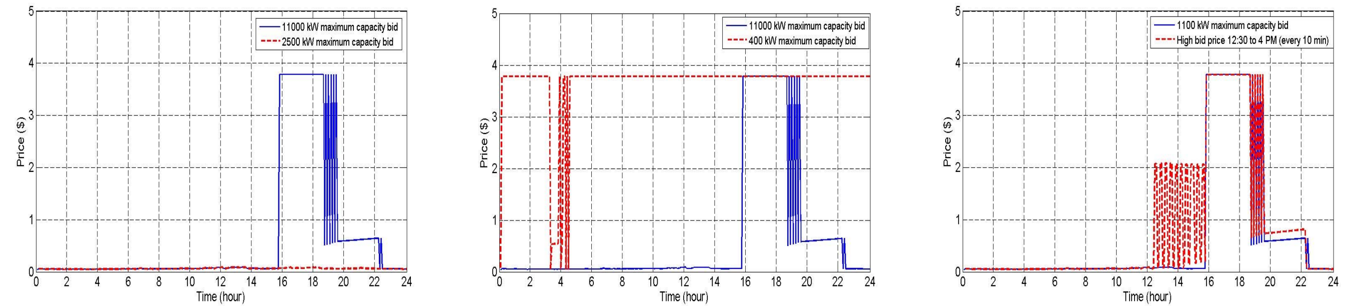
Fig. 7. Demand/Response Total Load

usage, increasing power generation costs and power losses, resulting in an economic gain for customers and a financial loss for the supplier.

False Data Injection – Low Capacity Bid (400 kW): Figure 7(b) shows the variation of total load for a normal capacity bid of 1100 kW and a low capacity bid of 400 kW, respectively. By injecting a false, small maximum capacity bid, we provide less power to the energy market relative to the average demand. As expected, energy contention is high and consequently, the real-time price is high regardless of the time of use. In these circumstances, attempts by end-users to adjust their energy use will have minimal impact and the market operation is less efficient. In addition, we observe that since the market was very congested during peak period, end-users tend to increase their energy usage after peak periods as the energy becomes more affordable. Because of energy contention, we can also observe that a very high real time price generates substantial profit for the supplier while increasing energy costs for end users. Nonetheless, the financial gain of the supplier is contrasted with the power losses due to high power generation costs.

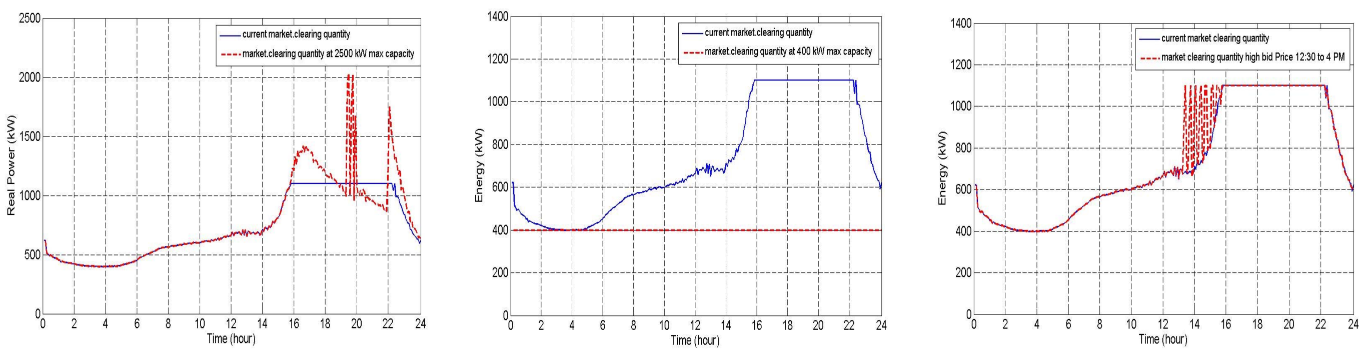
False Data Injection: High Bid Price: Figure 7(c) represents the variation of the total load when a false high bid price is injected from 12:30 pm to 4 pm. In contrast to the normal operation, we observe the intense fluctuations of the load as customers attempt to reduce their energy usage from 12:30 pm to 4:00 pm, which is the time when the false high bid price is injected. . Their energy usage then increases from 7 pm to 10 pm when the price has come down to normal. This shows the effectiveness of the power balance process as end-users intentionally reduce their power consumption when the price is high and increase it when the market is more affordable. Nonetheless, this scenario still creates disturbances, which are noticeable by the presence of high peaks.

Network Performance and Network Congestion: Figure 10(a) illustrates the variation of total load within the constraints of the communication network settings. The network is configured with the intent to create a poor performing network. The maximum data rate was set to 1 Mbps and the transmission delay set to 10 ms. In this configuration, the packet delivery ratio is very low as more packets are dropped. Both poor network performance and network congestion serve to disarticulate the market operation. The lack of a real-time information exchange between substations (suppliers) and end-



(a) Capacity Bid at 2,500 kW (b) Capacity Bid at 400 kW (c) High Energy Bid Price

Fig. 8. Market Clearing Price



(a) Capacity Bid at 2,500 kW (b) Capacity Bid at 400 kW (c) High Energy Bid Price -12:30 to 4 PM

Fig. 9. Market Clearing Quantity

users leads to a dysfunctional market, making the impact of demand response application to be not very noticeable. This makes a behavior similar to that of the traditional grid, which does not have demand response capability.

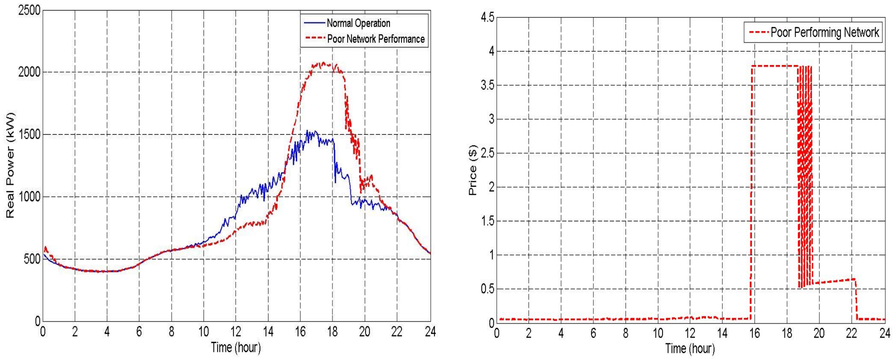
B. Energy Market: Market Clearing Price

Reference Bid Price: Figure 6(c) shows the variation of the energy reference bid price from the energy supplier over 24 hours. As we can see, the energy price is the highest during the peak hours from 12 pm to 1:30 pm and from 4 pm to 6 pm. During this period, price varies from \$0.05 to \$3.78 at peak time. Conversely, the energy price is relatively low, less than \$0.08 late at night and early in the morning.

Market Clearing Price for False High Capacity Bids: Figure 8(a) represents the variation of the market clearing price for a high capacity bid. A false maximum capacity bid of 2500 kW creates the opposite effect, in which the energy price is always affordable regardless of the time of use. As shown in the figure, the energy price with 2500 kW capacity bid is almost the same for low consumption and peak periods and remains below \$0.05. In this scenario, the gain of end users coincides with the significant loss of the energy suppliers. Manipulating and forging capacity bids can have tremendous impact on the market.

Market Clearing Price for False Low Capacity Bids: Figure 8(b) illustrates the variation of the market clearing price for a maximum capacity bid set at 400 kW. During normal operation (1100 kW maximum bid), the price stays below \$0.08 and reaches the maximum only during the peak hours between 4 pm and 7 pm. It is worth noting that during this high price period, users intentionally reduce their energy use in order to reduce energy costs. With a false maximum capacity bid of 400 kW, which is far below the average demand, contention is high on the small amount of energy available in the market, causing the clearing price to reach the maximum of 3.78 even during the period of low consumption between 3 am and 4 am. This scenario gives a large profit for the supplier, but significant losses for end users.

Market Clearing Price for False and unstable High Price Bids: Figure 8(c) shows the variation of the market clearing price when a high bid price is injected in the system every 10 minutes from 12:30 pm to 4 pm. This causes the price to fluctuate continuously. As shown in the figure, the fluctuation and instability of bidding price reflect directly on the market



(a) Total Load (b) Market Clearing Price

Fig. 10. Poor Network Performance

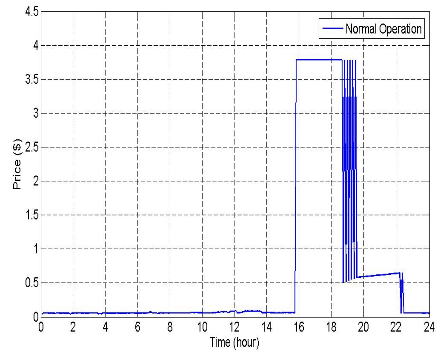
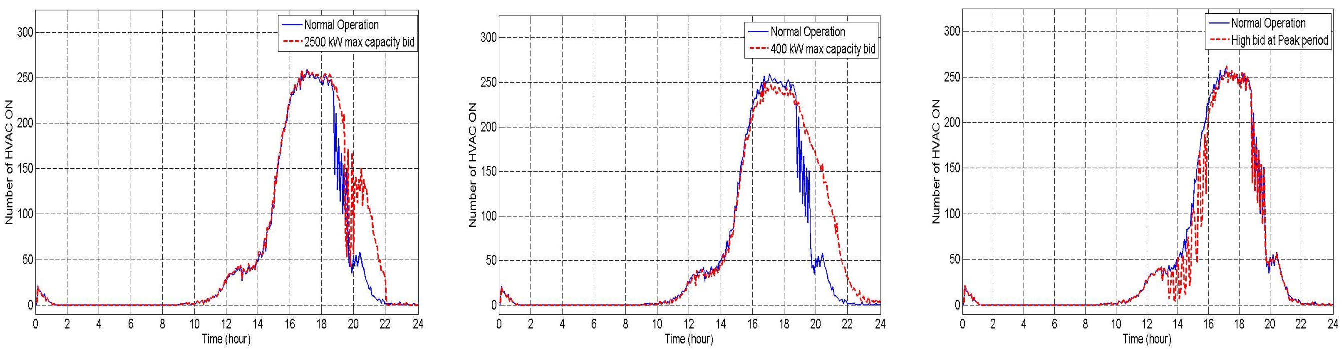


Fig. 11. Normal Clearing Price



(a) Capacity Bid at 2,500 kW (b) Capacity Bid at 400 kW (c) High Energy Bid Price -12:30 to 4 PM

Fig. 12. HVAC Population Statistics

clearing price.

Market Clearing Price with Network Congestion: Figure 10(b) illustrates the variation of the market clearing price with a poor performing or congested network. The result is a disarticulated energy market. The lack of a real time information exchange between substations (suppliers) and end users leads to a dysfunctional market. The clearing price is similar to the reference clearing price (Figure 11) as the substation barely gets any bid or feedback from end users.

C. Energy Market: Market Clearing Quantity

Market Clearing Quantity with a False High Maximum Capacity Bid: Figure 9(a) represents the variation of market clearing quantity over 24 hours for a false maximum capacity bid of 2500 kW. With a false maximum capacity bid of 2500 kW, the clearing market quantity increases during low and high peak hours as end users take advantage of the affordable energy rates.

Market Clearing Quantity with a False Low Maximum Capacity Bid: Figure 9(b) represents the variation of market clearing quantity over 24 hours for a false maximum capacity bid of 400 kW. With a false maximum capacity bid of 400 kW that is less than 1,100 kW of the normal operation and below basic end users' demand, the energy market is unable to maintain the energy clear quantity below the 400 kW limit. As a consequence, a too small capacity bid less than basic end users' energy demand has no significant effect on end users' energy usage and the total load could inevitably exceed the substation maximum capacity bid.

Market Clearing Quantity at False High Bid Prices: Figure 9(c) illustrates the variation of the clearing market quantity when a false high bid price is injected every 10 minutes between 12:30 pm and 4 pm. Users respond to the fluctuating bid price by adjusting their power demand every time when the price changes. This situation can be very disturbing for end users. The more unpredictable and unstable the market is, the more difficult it is for end users to efficiently adjust their energy use habits.

Economic Impact of Dynamic Markets: Figure 13 represents the comparison of one hour energy bill for a single house for different simulation scenarios. While the house used approximately the same amount of energy, a reduced maximum bid capacity incurs the most severe economic impact with a 189.24 percent increase or a financial loss of \$144.107 when compared to the normal scenario. In addition, confirming our

Scenario	Bill Amount	Energy	Gain/Loss
Normal Operation	76.150	56.833	N/A
Max Capacity at 400 kW	220.257	56.847	-144.107
Max capacity bid at 2500 kW	13.681	56.792	62.468
High bid price 12:30-4pm	86.453	56.833	-10.302
Network Performance	76.035	56.833	0.114
Network congestion	76.059	56.833	0.090

Fig. 13. Economic Impact of the Market for One Hour (Single House)

previous finding, a large maximum bid capacity is the most profitable for the end user with an 82 percent bill reduction or a gain of $62.468.

D. HVAC Population Statistics

Maximum Capacity Bid – 2500 kW: Figure 12(a) illustrates the variation of the number of HVAC systems running over time for a false maximum capacity bid of 2,500 kW. Because this is greater than the 1,100 kW for normal operation, there is more energy available and the market price drops. This motivates end users to use more energy and to keep their HVAC system running at low temperature setting points.

Maximum Capacity Bid – 400 kW: Figure 12(b) illustrates the variation of the number of HVAC systems that are ON in a 24 hour period when a false maximum capacity bid of 400 kW is injected to the grid. This is less than the average demand, meaning that the contention on biddable energy is high, which causes the real time energy price to significantly increase. Consequently, as shown in the figure, the number of HVAC systems running decreases during peak times (4 pm - 7 pm). After 7 pm, as the demand and the real-time price are falling, more HVAC systems resume their operation and thus the number of HVAC systems increases.

High Bid Price: Figure 12(c) represents the variation of the number of HVAC systems running over time when a false high bid price is injected between 2 pm and 6 pm. As shown in the figure, a high bid price during that specific time frame causes a lot of fluctuations in the HVAC population. Many HVAC systems are flip-flopping, going from ON to OFF in order to adjust their energy use and to contain the energy bill within a reasonable range. We observe that after 4 pm, the market returns to normal operation and the HVAC population follows the normal trend.

V. Conclusion

In this paper, we addressed the performance issue of the smart grid based on co-simulations. We systematically reviewed existing efforts of co-simulation and designed a framework to explore co-simulation scenarios. To understand the interaction and the reciprocal effects between the communication network and power grid in the smart grid, we investigated the performance of the demand/response and energy price (e.g., representative smart grid applications) and the communication network under various condition (e.g., normal operation, degraded performance, and security threats). By leveraging a known co-simulation platform, we developed co-simulation scenarios and conducted a performance evaluation of selected smart grid applications when the communication network is operating under various conditions. As ongoing work, we are investigating the performance of additional smart grid applications interacting with the communication network operating under various conditions.

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