

# A Multiagent Modeling and Investigation of Smart Homes With Power Generation, Storage, and Trading Features

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**Abstract**—Smart homes, as active participants in a smart grid, may no longer be modeled by passive load curves; because their interactive communication and bidirectional power flow within the smart grid affects demand, generation, and electricity rates. To consider such dynamic environmental properties, we use a multiagent-system-based approach in which individual homes are autonomous agents making rational decisions to buy, sell, or store electricity based on their present and expected future amount of load, generation, and storage, accounting for the benefits each decision can offer. In the proposed scheme, home agents prioritize their decisions based on the expected utilities they provide. Smart homes' intention to minimize their electricity bills is in line with the grid's aim to flatten the total demand curve. With a set of case studies and sensitivity analyses, we show how the overall performance of the home agents converges—as an emergent behavior—to an equilibrium benefiting both the entities in different operational conditions and determines the situations in which conventional homes would benefit from purchasing their own local generation-storage systems.

**Index Terms**—Energy storage, load management, multiagent systems, smart grids, wind power generation.

## I. INTRODUCTION

A POWER system, as a critical energy-providing structure, must continuously adopt new technologies in order to improve its efficiency in terms of reliable operation and cost. Smart grid is a general term recently used to label the emerging power grid resulting from current technological adoptions in power systems [1]. This new type of grid incorporates recent improvements in different areas of engineering and science and, for the most part, in communication and networking in order to operate more efficiently [2]. In addition, it accommodates new types of loads/generations such as electric vehicles/distributed generation.

Electricity providers need to continuously study the electricity demand and behavior of its customers in order to operate

a system reliably and to plan for the future. Because of the large number of electricity consumers diversely distributed in the system, it is difficult to grasp the overall aggregated behavior of the consumers. Therefore, utilities often use simulation-based methods to study the operation of a power system and to forecast future loads [3], [4].

With the advent of the smart grid and smart distribution systems (SDS), many recent studies have focused on simulating interactions between the smart home and the grid in regard to cost reduction [5] and load management through demand response (DR) [6]–[8]. However, the capability to generate and store electricity has not been included in any of this research. The authors in [6] have proposed a multi-layer demand response scheme that includes different types of customers. Optimum electricity consumption is determined in [7] within a home containing smart appliances and across multiple homes; however, the electricity price is assumed to be deterministic for the duration of the study. The authors in [8] aim to maximize the customers' utility within a real-time demand response model, but they do not investigate the effect of demand response on the grid side.

Most of the load management approaches used to look at the problem from the grid's perspective. With the smart grid, however, the bidirectional data flow and interoperability between homes and the grid have created an opportunity to optimize an individual customer's power consumption and, *at the same time*, enhance the overall system-wide operation of the grid through peak load alleviation. This is possible because the objectives of both the customers and the utilities are in agreement. Therefore, in recent years, more research efforts have focused on *distributed* approaches to demand-side management [9], [10].

Furthermore, distributed generation and battery storage systems are enabling homes and small businesses to benefit by selling excess power back to the grid as well. In the paradigm of the SDS, individual entities can continuously make rational decisions to buy, sell, or store electricity based on their present and expected future amount of load, generation, and storage, considering the benefits of each decision.

When it comes to distributed grid modeling, techniques based on multiagent systems (MAS) have been adopted due to their versatility, scalability, and ability to model stochastic and dynamic interactions among homes (as agents) and between a home and the grid. Indeed, there have been several MAS-based applications in the power system literature, such as electricity market [11], [12], voltage control [13], load restoration [14], load shedding [15], and the smart grid area [16]–[22].

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However, none of these models have fully utilized previously described smart home features. The research is either descriptive without any experiments [16], or the capabilities of the smart home are simplified and restricted to such an extent that the problem may even become solvable without an MAS design [17]. The inability of the home agents to generate power is among those restrictions [20]. The authors in [21] have provided a game-theoretic framework to find the best electricity storage strategy. This study results in an equilibrium point where the electricity prices are more flattened. However, to reach this point, customers are limited to gradually adapt their storage profile. In addition, no demand response scheme is studied in this paper. An efficient load management system, with green energy and conventional power suppliers, is proposed in [22], aiming to reduce electricity cost and carbon emissions. Nevertheless, the ability of customers to generate electricity, adjust their load based on the price signal, and sell electricity back to the grid has not been included in this paper.

In this paper, we propose and discuss smart homes that not only consume electricity but are also capable of generating and storing it using their own power generation and electricity storage system. Taking it one step further, we see these homes as smart and flexible as they make autonomous decisions to manage their load, generation, and electricity storage. Moreover, they can interact with the grid to trade electricity in a way that benefits them the most. We take the challenge of including unpredictability and dynamism introduced to the smart grid as a result of a large number of prosumers with varying demands and generation volatilities, each with their own aims and priorities, operating within an uncertain environment affected by the power system conditions and the outcomes of actions taken by individual households [23].

Our approach is to model the homes as *agents* in a smart grid environment. Each individual home agent tries to minimize its cost of electricity by making decisions from the following options: buy electricity from the grid, charge or discharge batteries, sell electricity to the grid, and, sometimes, ignore low priority loads. Decisions made by the homes affect the electricity market and *vice versa*. Therefore, sound decisions are critical to lead the entire system toward efficient, consistent operation. In our model, home agents autonomously make decisions by comparing the utilities of their available options. These utilities are calculated based on the agents' observations of current and predicted future conditions of the environment. Rational agents try to avoid buying electricity when the prices are high. Therefore, these strategies provide them with more savings on their electricity bills. By comparing several case studies, we demonstrate that our proposed model and the resulting distributed decisions made by households, enable electricity prices to be modified, and the emergent behavior of the system to move toward a flatter load curve which is desirable from the utility's perspective.

To the best of the authors' knowledge, the proposed model is the most comprehensive MAS-based model of SDS. Several case studies investigate the operation of the model provided and prove its efficiency for both utilities and customers through comparison of the corresponding evaluation metrics defined in this paper. It should be noted that although for sim-

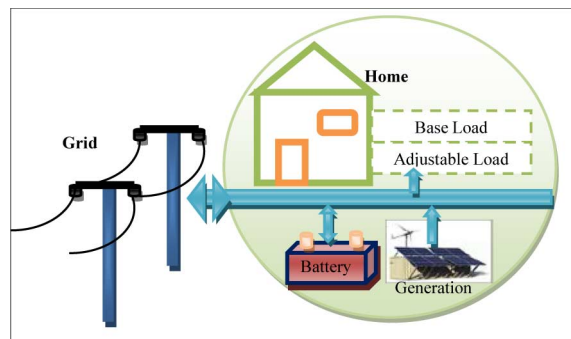


Fig. 1. Electricity flow between different sectors connected to a smart home.

licity we use *homes* to explain our method, the model developed is generally designed, and not necessarily targeted or limited to residential customers. The scheme can be applied to other types of customers with commercial or industrial loads, community-based energy development (C-BED) entities, or an interconnected structure of microgrids in the power system by simply adjusting the input parameters of the model developed.

The rest of the paper is organized as follows. Section II explains the overall configuration of the system and the tasks of a home agent. Section III describes the simulated model and provides detailed information about different components of the model. Then, several case studies and results are introduced in Section IV and V, respectively. Section VI provides the conclusion of the paper, and we discuss our intended future work in Section VII.

## II. PROBLEM STATEMENT AND THE APPROACH

This paper provides a design for a model of the future smart grid that aims to minimize power costs for the homes and alleviate the overall peak load of the system during operation.

To accomplish this goal, the power grid is modeled as a multi-agent system comprised of  $N$  home agents distributed within the environment. Each home has a variety of appliances that consume electricity, called *home loads*. Homes also own a small *generation-storage system* consisting of wind turbines generating electricity based on the stochastic wind speed and batteries storing electricity. The *grid*, as the main provider of electricity, is responsible for balancing the amount of load and generation. It sells the needed amount of electricity to the homes at the purchasing rate and buys their surplus electricity at the selling rate.

In a smart grid environment, homes can be modeled as agents who decide whether to buy, sell, use, or store electricity at any point in time by comparing the utilities associated with each of these options. Decisions are made in time intervals of 1 h for our model. Fig. 1 shows different entities of the model as well as possible directions of electricity flow, illustrated by the arrows.

Each hour, agents use data about their own loads and determine the priority of that load by assigning a *Load Utility*. The agents then observe the environment to obtain the current wind speed and the electricity price for that hour. Home agents are also equipped with a tool to model their predicted future load, generation, and the electricity price. Using these parameters, the home agent computes its utility of storing the electricity, *Store*

*Utility*, or selling the available generation to the grid, *Selling Utility*. Based on a comparison of these utilities, which are normalized between 0 and 1, the agents make their decision for the current hour. A detailed description and the equations for utility calculation will be given in the following sections.

Each hour, the agent will encounter one of the following: a *generation surplus* or a *generation deficit*. A *generation surplus* occurs whenever the amount of electricity generated is higher than the amount of the load demand, and a *generation deficit* occurs when the load demand is greater than the amount of electricity generated. When a home agent is in generation surplus mode, it looks for the most profitable decision between three possible options: supplying the load, charging a battery, and selling to the grid. It chooses the option with the highest utility. On the other hand, if the home agent is in the *generation deficit* mode, it aims to manage the situation at the lowest possible cost, which means the agent searches for the decision with the lowest associated utility to take care of the electricity deficit. If it turns out that the lowest utility belongs to its own load, i.e., load utility is the minimum, the agent will reduce the load for that hour because the utility implies that the load is not having a high enough priority. This models the demand response directed by the home agent. Load reduction may be managed by adjusting the thermostats, and turning off the lights and low priority appliances. The capability of shifting the load in time is not modeled in this study.

There are several assumptions regarding customers' electricity trade with the grid. Each hour, there are two electricity rates defined: one is the rate at which customers purchase electricity, and the other one is a lower rate at which they can sell electricity back to the grid. In fact, a real-time pricing scheme has been modeled in this paper where the price signal announced by the grid reflects the demand based on a model of the electricity market that will be described in detail, later in Section III-B. In addition, it is assumed that although there is no limit on the amount of power available to be purchased from the grid, there is a limit on the amount of power available to be sold to the grid at each hour.

In a case where the demand is low and the grid is in a generation surplus state, electricity rates are lower; and as needed by the grid, homes have less incentive to sell back their generation. Besides, surplus generation can be prevented by proper selection of the hourly buyback limit by the grid. It should be mentioned that our model is still simplified and may not address all of the issues raised by the grid's supply and demand conditions.

Consequently, we expect that by providing a distributed decision-making environment and enough incentives for the home agents, they can make decisions so that their households save on electricity costs; and at the same time, the overall emergent behavior of the system leads to a more flat aggregated electricity purchase from the grid.

### III. MODEL DESIGN

This section describes the different models and aspects of our simulated smart grid system. This system has been implemented using Repast Simphony software [24] based on the Java programming language. Repast Simphony is the latest version of Repast (REcursive Porous Agent Simulation Toolkit), a powerful tool designed to provide a visual platform for an agent

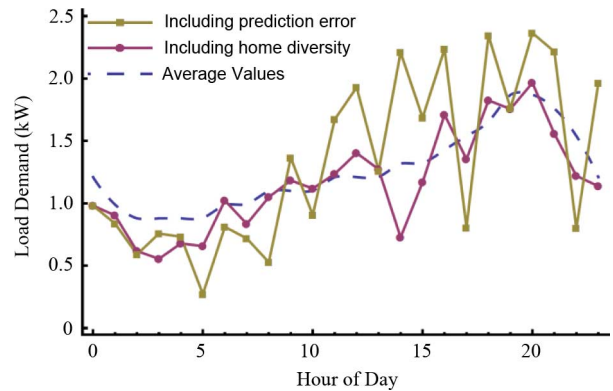


Fig. 2. The average load, the output of the RM for diversity consideration, and the output of the RM for up to 24-h ahead prediction.

model and spatial structure design, agent behavior specification, model execution, and results examination [25].

Our design in Repast Simphony is comprised of the random models, environment, agents, decision variables, and system evaluation metrics used for this study.

#### A. Random Models (RMs)

We use random models (RMs) for two main applications in our research. First, we use an RM to represent the diversity of loads, wind generation, and battery storage of different households based on a predetermined probability distribution. This includes modeling different household behaviors in electricity consumption through the *load utility* at each hour. Second, we also use an RM to represent a household's short-term prediction of the load, generation, and electricity rates in the next few hours. Precise and detailed forecasting of the variables is out of scope of this paper, but instead we include the uncertainty in forecasting these variables, using the random model. For this application, a logarithmic function is defined which adds more deviation to the average value of a parameter of interest, as the look-ahead time for predicting this parameter becomes larger. Therefore, the accuracy of the prediction depends on how far in the future a parameter is being predicted.

A random model can be either a *data-based model* (DBM) or a *function-based model* (FBM). A DBM generates random values based on actual data corresponding to the average value of the property being modeled. An FBM, on the other hand, generates random values based on a mathematical model representing the average value of the property of interest.

In our design, a household's wind generation and loads are determined by a DBM, where the average values of wind speed and load for each hour are provided as inputs to the model. Electricity rates are calculated based on an FBM, where an exponential function is used to express the retail price of electricity based on the power purchased by the homes.

Equation (1) defines the output of RM for both DBM and FBM at hour  $t$  provided that the current hour is  $t_0$ .

$$\Gamma(t) = N(c_1 \cdot \psi(f(t)), c_2 \cdot \log(t - t_0 + 1)) \quad (1)$$

where  $N$  represents the normal distribution; and  $\psi$  can be any probability distribution function corresponding to  $f(t)$  which defines the average value of the property to be modeled at time  $t$ . Real constants,  $c_1$  and  $c_2$ , are predetermined. In fact, the RM uses a normal distribution with a mean corresponding to some

scaling of the parameter's base function and a standard deviation which increases with  $t$  and mimics the possible error of prediction of that parameter ahead of time.

For example, assuming that hour 0 is the current time, Fig. 2 shows the average load value and the output of the RM used in our study, with  $c_1 = 1$  and  $c_2 = 0.15$ , respectively.

### B. Environment and the Agents

Environment is a critical part of the MAS. This is where agents obtain their observations and perform their actions. There is one grid agent and  $N$  home agents in this environment. Home agents know about their load and have access to wind speed and electricity price as stochastic variables of the dynamic environment.

- *Wind Speed*

Each hour, the amount of electricity generated by each home is calculated based on the home's wind turbine characteristics and the wind speed at that hour. We have modeled wind speed using a DBM and considering  $\psi$  as a Rayleigh distribution [26]. The average hourly wind speed data are the input of the RM. Further, using the manufacturer-provided power curve for a wind turbine, the expected power output for a given wind speed is calculated. Peak electricity demand often happens in the evening, but the high amount of wind generation does not usually coincide with the peak load. So the home agent should wisely decide on how to store and consume the electricity it has generated.

- *Electricity Rates*

Another dynamic attribute of the environment is the electricity purchase rate (EPR) calculated as a function of the household's electricity demand from the grid. There are two rates associated with each hour: the announced rate before the submission of the household's electricity demand,  $EPR(t^-)$ , and the actual rate after the demand requests have been received by the utility,  $EPR(t)$ .

Due to the correlation between the prices of electricity per hour in nearby consecutive days [9], the announced electricity rate is modeled based on the weighted sum of past days' electricity rates at the same hour, as expressed by (2):

$$EPR(t^-) = \sum_{d=1}^m k_d \cdot EPR(t - 24 \cdot d); \quad \sum_{d=1}^m k_d = 1 \quad (2)$$

where  $k_d$  is the weighting factor to model the correlation between the price on the current day and that on  $d$  days ago; and  $m$  is the number of days to be included from the past.

Actual electricity rates are modeled according to an FBM in which  $f(t)$  is replaced with  $EPR(t)$ .  $EPR(t)$  represents the modeled electricity market by fitting a typical set of points (electricity price, load demand) [21] into a monotonically increasing function and normalizing it for each household, as expressed by (3):

$$EPR(t) = \alpha_1 \cdot e^{\alpha_2 \bar{l}(t)} + \alpha_3 \cdot e^{\alpha_4 \bar{l}(t)} \quad (3)$$

where  $\alpha_1$  to  $\alpha_4$  are coefficients of the fitted function and  $\bar{l}(t)$  represents the actual load demand of the average household for hour  $t$  in kWh.

The *EPR* specifies the rate at which households can purchase electricity from the grid. On the other hand, households with generation-battery systems may sell their excess electricity to the grid at the electricity selling rate (ESR), which is lower than the EPR.

- *Home Agents*

Home agents are the actual agents of the system. Each home agent includes the following properties: 1) the load demand, 2) the priority of the load demand (*Load Utility*), 3) the wind power generated, and 4) the amount of available electricity storage.

Random modeling provides a household with the opportunity to include uncertainty in their predicted values of demand, generation, and electricity rates. With this information, a home agent then computes both *Selling Utility* and *Store Utility* for each hour (Section III-C). Home agents manage their load, generation, and the battery based on the associated utilities they compute at each hour.

- *The Grid*

The grid is modeled as a simple agent that balances the generation and the load at each hour, i.e., it buys the surplus generation of the homes or sells to them the amount of their electricity demand. The amount of sold-back power by each home agent  $i$  ( $sell_i(t)$ ) may, however, be limited due to the grid operation constraints related to load flow and power system stability considerations.

$$sell_i(t) < sell_{max}. \quad (4)$$

### C. Decision Utilities

As previously introduced in Section II, there are three utilities used by the agents to assign priorities to decision options of a home agent. The utilities are all normalized values between 0 and 1, so home agents are able to compare these values directly without adjustments. In a case where a restriction occurs, preventing the execution of the decision with the winning utility, the next highest priority decision will be selected to avoid any constraint violations in the system. Examples of these restrictions are the maximum power purchased by the grid and the maximum available charging capacity of the battery. In this section, the utilities are described in more detail.

- *Load Utility (LoU)*

*Load Utility* is a random number between 0 and 1 based on uniform distribution and models the priority of the load to be satisfied at a specific hour relative to other decision utilities. In fact, load priority evaluates home agent's behavior and preferences. The actual value of this utility depends on many other factors which are not in the context of this study. In this paper, diversity of the homes has been modeled by different load priorities using a RM with a normal distribution at each hour.

- *Selling Utility (SeU)*

*Selling Utility* represents a home agent's incentive to sell its excess electricity to the grid. *SeU* is defined so that as it decreases, there will be more motivation to buy from the grid instead of selling to it. Equation (5) is empirically derived for each household  $i$  based on the fact that a home

benefits more from selling back to the grid whenever it has additional generation and the electricity rate is higher.

$$SeU_i(t) = \begin{cases} \sqrt{\frac{ESR(t^-)}{\max_{t \leq t' < t+\tau} (ESR^P(t'))} \cdot \frac{(g_i(t) - l_i(t^-)) \cdot ESR(t^-)}{\max_{t \leq t' < t+\tau} ((g_i^P(t') - l_i^P(t')) \cdot ESR^P(t'))}} & \text{if } g_i(t) > l_i(t^-) \\ \frac{EPR(t^-)}{\max_{t \leq t' < t+\tau} (EPR^P(t'))} & \text{if } g_i(t) < l_i(t^-) \end{cases} \quad (5)$$

where  $g_i(t)$  and  $l_i(t^-)$  are the amount of wind generation and the initial load of household  $i$ . In fact,  $l_i(t^-)$  is the output of the load RM, similar to the one shown in Fig. 2 at time  $t$ . Index  $P$  identifies the predicted variable which is derived based on RM, and  $\tau$  is the desired foreseen duration for utility calculation. If the generation of a home for the current hour is higher than the load ( $g_i(t) > l_i(t^-)$ ), there will be a high incentive to sell that power to the grid because either that home has a large generation or the current ESR is higher than its future's predictions. A geometric mean is used to include both parameters and keep the utility within the defined limits. On the other hand, if the generation is less than the load ( $g_i(t) < l_i(t^-)$ ), the home agent should buy from the grid when the cost of supplying the remaining demand is low enough compared with the future predicted costs.

To compute  $SeU$ , home agents obtain the current hour selling price,  $ESR(t^-)$ , from the grid and use RM to predict the required variables for the duration of  $\tau$ . Higher values of  $SeU(t)$  imply that, by selling to the grid at the current hour  $t$ , households get more benefit than if they wait to sell at future hours.

- *Store Utility (StU)*

*Store Utility* represents a home agent's incentive to store electricity. With a similar approach to what was described for the *Selling Utility*,  $StU$  is defined by (6) which can be perceived as an analogous to (5) except that all of the parameters used here are estimated future values.

$$StU_i(t) = \begin{cases} \frac{\text{Average}_{t < t' < t+\tau} (ESR^P(t'))}{\max_{t < t' < t+\tau} (ESR^P(t'))} & \text{for all } g_i^P(t') > l_i^P(t'), t < t' < t + \tau \\ \sqrt{\frac{\text{Average}_{t < t' < t+\tau} (ESR^P(t'))}{\max_{t < t' < t+\tau} (ESR^P(t'))} \cdot \frac{\text{Average}_{t < t' < t+\tau} ((l_i^P(t') - g_i^P(t')) \cdot EPR^P(t'))}{\max_{t < t' < t+\tau} ((l_i^P(t') - g_i^P(t')) \cdot EPR^P(t'))}} & \text{for all } g_i^P(t') < l_i^P(t'), t < t' < t + \tau \end{cases} \quad (6)$$

where averaging is utilized to capture the overall trend of the predicted decision variables in the future. Generally, agents may want to store electricity in order to sell it to the grid if they expect to generate enough electricity in the future ( $g_i^P(t') > l_i^P(t')$ ) at a high price. If the expected generation is less than the expected load ( $g_i^P(t') < l_i^P(t')$ ), agents will be willing to store electricity if they predict

having a large power deficit or high electricity rate in the future.

#### D. Evaluation Metrics

Three evaluation metrics have been defined where the first two parameters are from the grid perspective, and the last one is from the household's point of view.

As mentioned earlier, the desired state of the smart grid is to have an overall flattened aggregated power demand from all of the households supplied by a utility. Two metrics have been defined in this paper to evaluate the overall behaviour of the system as individual home agents are making their own autonomous decisions.

- *Demand Deviation (DD)*

Demand deviation evaluates the mean fluctuations of the overall electricity demand; and it is calculated by dividing the standard deviation ( $STD$ ) of the set of demands from the grid over a window of the past 24 h by the number of home agents,  $N$ .

$$DD(t) = \frac{STD(\{L(t')\}, t - 24 < t' < t)}{N} \quad (7)$$

where  $L(t')$  is the total electricity purchased from the grid at hour  $t'$ . Lower values of  $DD$  are preferred because it suggests less demand variations.

- *Diversity Factor (DF)*

Diversity Factor captures the diversity of the homes' peak demands, and it is defined as the ratio of the sum of the individual peak demands of the households to the maximum total demand over a window of the past 24 h.

$$DF(t) = \frac{\sum_{i=1}^N \max_{t-24 < t' < t} (l_i(t'))}{\max_{t-24 < t' < t} (L(t'))} \quad (8)$$

Higher values of  $DF$  are more valuable from the grid's point of view, because they imply that home agents' peak demands are more distributed in time and do not coincide.

- *Home Cost of Electricity (HCOE)*

The electricity cost of a home  $i$  evaluates the local performance of the home agents. The electricity cost shown by (9) is derived by summing four terms representing the cost of purchasing electricity, minus the income of selling, cost of the battery, and cost of home generation.

$$HCOE_i(t) = l_i(t) \cdot EPR(t) - s_i(t) \cdot ESR(t) + C_G \cdot g_i(t) + C_B \cdot Cap_B \quad (9)$$

where  $l_i(t)$  and  $s_i(t)$  are the amount of power bought/sold from/to the grid, respectively.  $C_G$  is the levelized cost per kWh of wind generation  $g_i(t)$  and  $C_B$  is the levelized cost per unit of battery capacity ( $Cap_B$ ) per unit of time, over their lifetimes.

## IV. CASE STUDY

Five case studies in this paper demonstrate the performance of our proposed system for both the households and the grid. In the first three cases, households with different capabilities are defined and compared with each other from both grid and

TABLE I  
INPUT PARAMETERS OF THE CASE STUDY

Parameter	$N$	$\tau$	$k_1$	$k_2$	$k_3$	$k_4$	$k_5$	$k_6$	$k_7$
Value	500	12	0.18	0.15	0.14	0.13	0.12	0.13	0.15
Unit	-	Hours	-	-	-	-	-	-	-
Parameter	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\overline{Cap}_B$	$\overline{Cap}_G$	$LoU$	$sell_{max}$	$\frac{ESR}{EPR}$
Value	2.3	0.6	0.3	2.5	1500	600	0.65	600	0.8
Unit	-	-	-	-	Wh	W	-	W	-

customer perspectives. Having the smart home modeled, in the latter two cases, a number of sensitivity analyses are performed to capture the behavior of the home agents and the power system under different circumstances. Each case study has a transient phase in which home agents make autonomous local decisions in interaction with the grid environment; and eventually, the overall performance of the system will reach equilibrium.

For our case studies, several input parameters defined are shown in Table I where  $\overline{Cap}_B$ ,  $\overline{Cap}_G$ , and  $LoU$  are average battery capacity, wind turbine capacity, and load utility of the homes, respectively. For the RM of the wind speed, hourly average wind speed data were derived for the city of Kimball, Nebraska, with an average wind speed of about 5 m/s at a height of 10 m [27]. The average load demand of the home agents was selected based on average residential electricity consumption of a typical U.S. home [28]. The electricity rates announced by the grid are calculated by (2) based on a 7-day history with weighting factors of  $k_1$  to  $k_7$  [9], and by (3) with parameters  $\alpha_1$  to  $\alpha_4$  where the minimum price of electricity is assumed to be 2.25 cents/kWh based on some typical data from [29].

In addition, we consider a number of assumptions for the operation of the battery storage system. The maximum rate of charge/discharge of the battery is set to 1 kWh/h; and the minimum percentage of remaining charge inside the battery, denoted by state of charge (SOC), is assumed to be 20% for its proper operation [30].

## V. RESULTS

The operation of a conventional home is studied in the first case. Then, by adding generation-storage capability and considering load priorities in Cases 2 and 3, the performance of the home agents in different cases will be evaluated and compared with each other.

### A. Case 1: Homes Without Generation-Storage Capability

In this case, we study the operation of conventional homes without wind generation and energy storage capabilities, homes that are not able to sell any power back to the grid. In addition, homes cannot make decisions because  $LoU$  is assumed to be 1 which results in supplying the total load, and none of the previously introduced  $SeU$  and  $Stu$  is sensible in this case.

Fig. 3 shows the amount of power bought from the grid and electricity rates for an average home within three days. Due to the homes' inability to respond to the price signal, the demand of the homes is not modified; and it is the same as power bought from the grid. As a result, electricity rates rise up as high as 40 cents per kWh at peak load hours in this case. In summary, the results shown here serve as a verification baseline for our later comparisons.

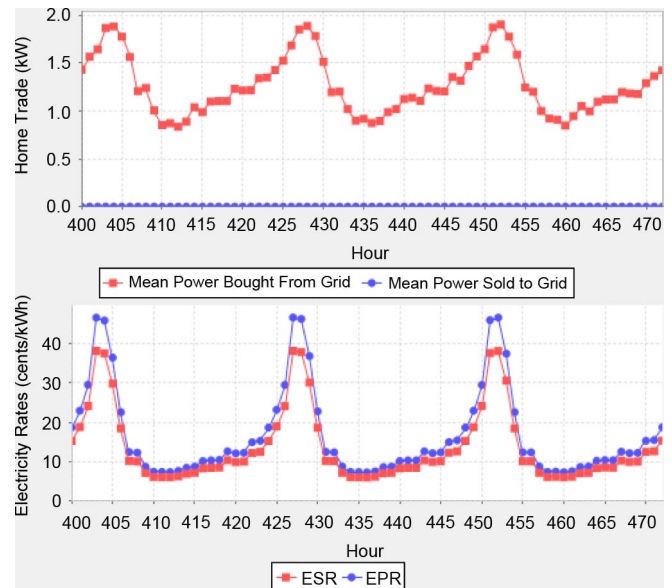


Fig. 3. Power demand from the grid (top); and the electricity rates (bottom) for the average household in Case 1.

### B. Case 2: Homes With Wind Generation-Battery System

In this case, we add wind generator and battery storage systems to the homes. As a result, home agents are able to make decisions to buy, store, or sell electricity. Similar to the previous case, loads have the highest priority and should be 100% satisfied.

Distributed decisions made by the home agents generate diverse behaviors which eventually converge to an equilibrium point depicted by Fig. 4. Wind generation, stored power, and the load of an average home are shown in Fig. 4 (top). The average load is similar to the previous case; and the wind generation is stochastic, based on the wind speed data. It is observed that the peak value of wind generation of an average home usually occurs at low demand hours and, therefore, cannot alleviate the peak demand by itself. However, using their storage capacities, home agents make proper decisions of storing, selling, or buying electricity based on calculated utility functions. Fig. 4 (top) illustrates that an average home agent decides to charge its battery, either by its own generation or the electricity bought from the grid, prior to the peak demand by predicting this need in advance. Then, the agent keeps the stored power to be used at peak hours, and hence avoids purchasing at high electricity rates. It also sells its excess generation to the grid usually when the local generation is high enough and the battery has sufficient charge. As a result, *an average home agent is able to decrease its peak demand by 30% and benefit from selling electricity* as displayed in Fig. 4 (middle). Consequently, the peak electricity rate is considerably reduced compared with the rate in the previous case (bottom): 12.5 cents/kWh or lower versus 48 cents/kWh or lower.

### C. Case 3: Homes With Wind Generation-Battery System and Load Priority Consideration

Households in this case are similar to Case 2 in wind generation-storage capability. The difference is that the load utility could be less than 1 and that allows for having some part of the load ignored by the home agent when this decision is relatively

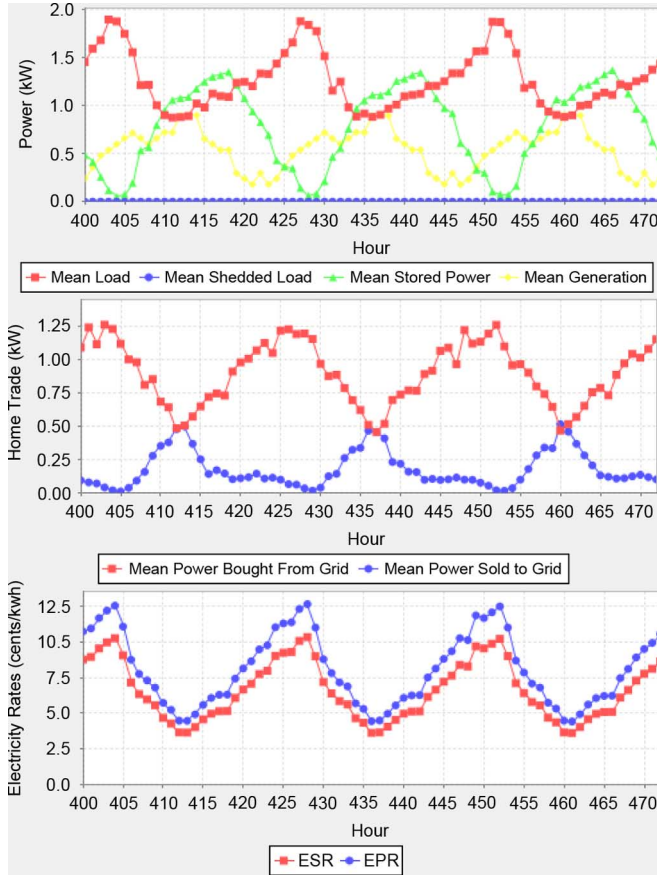


Fig. 4. Load, generation, and storage of the home (top); power trade with the grid (middle); and the electricity rates (bottom) for the average household in Case 2.

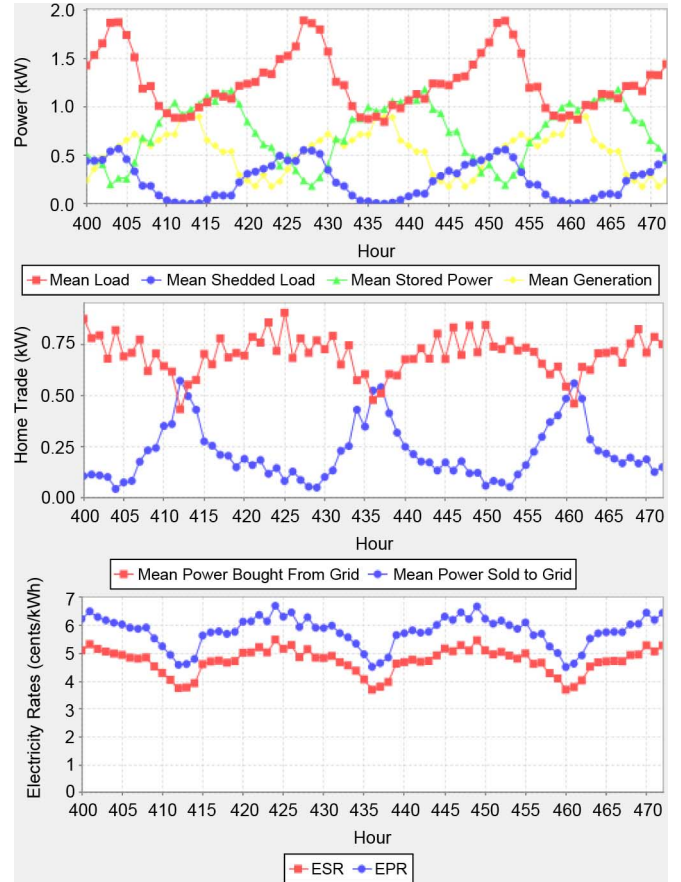


Fig. 5. Load, generation, and storage of the home (top); power trade with the grid (middle); and the electricity rates (bottom) for the average household in Case 3.

preferred over the other options. Here, it is assumed that in a case of electricity deficit and when  $LoU$  is relatively lower than the other two utilities, the load can be reduced to 50% as an active demand response. The results are provided in Fig. 5.

The top graph indicates that at high demands, an average home decides to reduce its demand by turning off part of its load. The reason is that, during peak hours, the cost of electricity is higher, which causes the other decision utilities to stay higher than  $LoU$ . As a result, home agent sacrifices part of its load, which is perceived to retain the lower priority at that time. Fig. 5 also shows that by manipulating the load, electricity rates flatten more compared with the previous two cases. Here, an average home agent is able to decrease its peak demand by 25% compared with the previous case.

As previously mentioned, home agents make autonomous decisions which eventually lead to equilibrium as an emergent behavior of the system for all of the cases. For example, Fig. 6 captures the dynamic characteristics of approaching the steady state condition, which is observed after the 100th hour, for Case 3 decision utilities based on which home agents make their decisions and reduce their electricity cost.

The effect of these distributed decisions is flattened electricity rates as an emergent behavior of the system after a few days.

#### D. Comparison of Cases 1, 2, and 3

The previous three cases are compared based on the evaluation metrics defined. According to Fig. 7,  $DD$  and  $DF$  are both

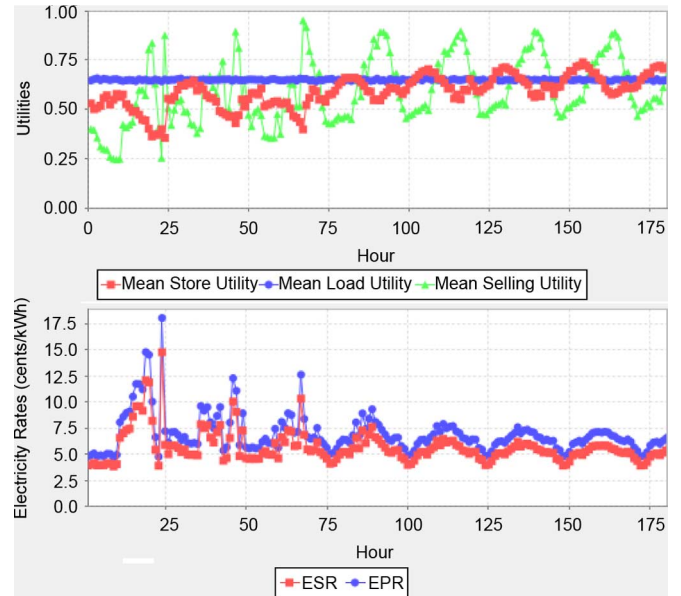


Fig. 6. Dynamic behavior of decision utilities and electricity rates in Case 3.

improved as we move from Case 1 toward Case 3. Based on the definition, a decrement of  $DD$  indicates that the demand of an average home is getting flatter in Cases 2 and 3 as hoped. In addition, incorporation of the generation-storage system and decision utilities provides more diversity for home agents in Case 2 in comparison with Case 1, and also, different load priorities

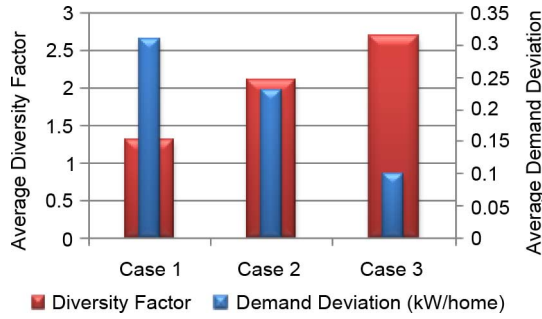


Fig. 7. Comparison of DD and DF for the average home.

TABLE II  
COMPARISON BETWEEN THE NORMALIZED ELECTRICITY COSTS OF THE AVERAGE HOUSEHOLD IN DIFFERENT CASES

Normalized HCOE for the average household (cents/kWh)	Case 1	Case 2	Case 3
	19	7.5	5.77

TABLE III  
COMPARISON BETWEEN THE NORMALIZED ELECTRICITY COSTS OF THE AVERAGE HOUSEHOLD WITH CONSTANT ELECTRICITY RATES

	Case 1	Case 2	Case 3
Constant electricity rate (cents/kWh)	19	10	7.5
Normalized HCOE for the average household (cents/kWh)	19	8.69	6.85

cause home demands in Case 3 coincide less than Case 2. As a result,  $DF$  rises from Case 1 to Case 3.

Another comparison is made among *normalized* HCOE of the three analyzed cases. The direct comparison of HCOE is not intended in this case, because the decreasing of cost in Case 3 is partially due to “not consuming” electricity. The Normalized HCOE is the cost of electricity per average amount of load satisfied by the home agent. The electricity cost of the average home is calculated based on (9) with the following base values for the leveled cost of battery and wind generation [31], [32].

$$C_B = 0.48 \text{ cents per kWh of capacity per hour}$$

$$C_G = 3.6 \text{ cents per kWh of power generation}$$

The results, provided for Cases 2 and 3 in Table II, indicate that the imposed cost of a generation-battery system in these cases is lower than the savings due to peak demand reduction. The cost of electricity is cut down as a result of lower electricity rates in Cases 2 and 3. However, moving from Case 1 to 2 provides more savings than from Case 2 to 3; because the model of the electricity market lies on an exponential curve and the difference is more noticeable at higher demand values.

#### E. Comparison of Cases 1, 2, and 3 With a Constant Electricity Rate

This study compares the electricity costs of Cases 1, 2, and 3 where the electricity rates are constant. Since the electricity demand is not similar in these cases, the constant rates for them are different and calculated to be equivalent of our real-time pricing scheme from the grid’s perspective. Table III provides these constant rates and the results.

Here, Normalized HCOE is the same as the constant electricity rate in Case 1, but homes can reach lower electricity costs

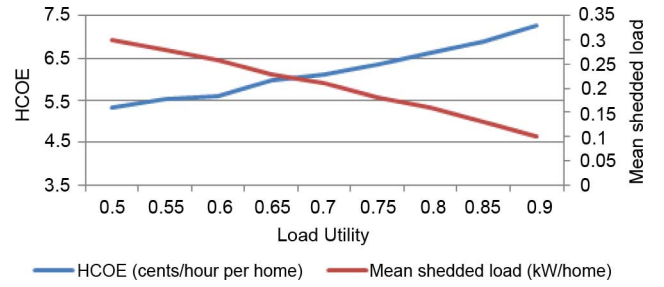


Fig. 8. Comparison of the electricity cost and mean shed load for the average home with different load utilities.

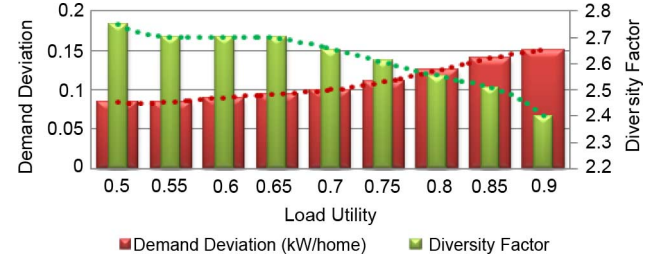


Fig. 9. Comparison of DD and DF for the average home with different load utilities.

in Cases 2 and 3. The main reason is that, in Case 1, the total demand is directly bought from the grid, and the home agent has no means to reduce the electricity cost. On the other hand, homes in Cases 2 and 3 have their own generation-storage system and can compensate for part of the load.

Comparison of Normalized HCOE in Tables II and III indicates that smart homes in Cases 2 and 3 perform better with real-time pricing than with a constant rate plan; because in the current case, unless the home agent has generation surplus, it does not have an incentive to store electricity to be used in the future and/or sold back to the grid because electricity rates do not change. However, wind generation and demand response are still effective in reducing the total demand and the electricity cost of a smart home.

Another outcome of this study is that the new customers, with a constant electricity rate plan, can find out that owning distributed generation-battery systems is beneficial for them because the costs of electricity for Cases 2 and 3, including the leveled cost of battery and wind generation, is less than the corresponding constant electricity rates announced by the grid.

#### F. Case 4: Sensitivity Analysis With Respect to Load Utility

In this case, the average  $LoU$  is changed; and the results are presented in Figs. 8 and 9. As expected, by increasing the average  $LoU$ , fewer loads are discarded and the electricity cost of an average home will be higher because it needs to purchase more electricity. According to Fig. 9, system performance deteriorates as the average home assigns higher priority to its load demand at the desired time. In this figure,  $DF$  starts to decrease with a higher slope for the  $LoU$  values higher than 0.7. According to Fig. 6, this is the point where the average  $LoU$  goes above  $StU$  having no more intersection with it; and on average, home agents become relatively less likely to ignore their load or store electricity for future needs. This provides less flexibility for the home agents to alleviate their peak demand; and, therefore, system evaluation metrics worsen.



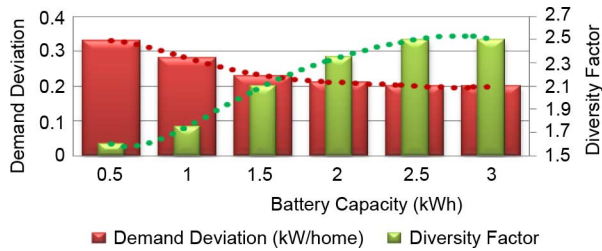


Fig. 10. Comparison of DD and DF for the average home with different battery capacities.

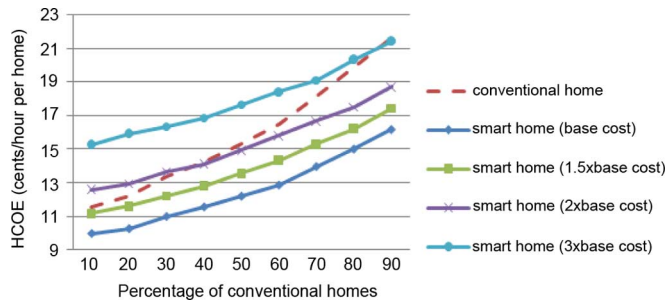


Fig. 11. HCOE in a power system with various percentages of conventional homes and different wind generation-battery costs for smart homes.

### G. Case 5: Sensitivity Analysis With Respect to Storage Capacity

Demand deviation and diversity factor are compared with different battery capacities in a situation where 100% of the load is satisfied. As shown in Fig. 10, the evaluation metrics show better performance with higher battery capacities. However, this improvement eventually reaches a saturation point (2.5 kWh in this study); because parameters such as average load of the system, wind generation capacity, and the limit on the amount of power sellable to the grid make larger batteries ineffective. On the other hand, at this point, HCOE starts to rise as the cost of additional battery capacity dominates the benefit of more storage capacity due to the mentioned limits. Considering both the electricity cost and performance metrics, a battery capacity between 1.5 and 2 kWh seems to be the most suitable for an average smart home in our system.

### H. Case 6: Sensitivity Analysis With Respect to Percentage of Homes With a Wind Generation—Battery System

In fact, there is a transition between the power grid consisting of conventional homes to the one with smart homes owning distributed generation-battery systems. The behaviors of different types of homes affect the electricity rates and cost of electricity. Analysis of Case 6 determines how the average electricity costs of both conventional and smart homes change with different combinations of homes in the grid.

Fig. 11 shows the results as the percentage of conventional homes in the grid changes from 10% to 90% with different costs for wind generation-battery systems for smart homes where the base cost is as defined in Section V-D. As more conventional homes are replaced with smart homes, both types of homes benefit from reduced electricity rates, due to operation of smart home agents doing local electricity management in the grid. It is noticeable that with the increasing percentage of smart homes, the decreasing rate of the cost is faster for conventional homes;

because they do not have a distributed generation-battery facility for which they would have to pay.

An interesting outcome of this study is to determine when investing in a generation-battery system is beneficial for the conventional home. According to Fig. 11, with a cost of  $2 \times$  base for a generation-battery system, it is worth switching to a smart home if the percentage of conventional homes in the grid is more than 40%. Fig. 11 illustrates that the result will change with different costs of generation-battery systems; for example at a cost of  $3 \times$  base, the electricity cost of a smart home is usually higher than the one for a conventional home, which makes the switch from a conventional to a smart home unprofitable. On the other hand, with the generation-battery cost of  $1.5 \times$  base and less, it is almost always beneficial to switch to a smart home no matter what percentage of the homes in the grid are conventional.

## VI. CONCLUSION

To study the performance of the power distribution system in transition toward a smart grid, we modeled smart homes as autonomous agents considering the power grid as a dynamic multiagent system. Smart homes were designed to have their own electricity generation and storage system. Using random models, the randomness of a home's electricity consumption behavior, wind generation, and the grid's electricity rates were taken into account. Assigning different utilities to its decision options, a home agent prioritized them similar to an electricity management scheme. This scheme worked effectively by indicating how a household should buy, store, sell, or use electricity in order to minimize electricity bills. In addition, smart homes had the chance to interact with the grid to trade electricity in a way that would benefit them the most.

Demand deviation and diversity factor from the grid's perspective and cost of electricity from the perspective of the homes were defined to evaluate the performance of the proposed model at both sides. Several case studies consisting of different types of homes were studied and compared with each other. As a result of home agents' individual decisions, we observed a transition period associated with each simulation followed by equilibrium as an emergent behavior of the agents. Results showed that home agents could successfully reduce their electricity costs by managing their load, generation, and storage, and at the same time, alleviate the total peak demand from the grid. Considering the cost of electricity generation and storage, we also determined the situation in which conventional homes would benefit from purchasing their own local wind generation-storage system.

## VII. FUTURE WORK

The model for the residential homes can be applied to different types of loads, including industrial and commercial customers, or a community of them, without loss of generality. We plan to derive the optimum generation and storage capacities to minimize electricity costs for the customers by incorporating a stochastic and artificial-intelligence-based optimization method into our model. We are also working on including neighbor-to-neighbor electricity trade by setting up a communication layer among the customer agents. Some other opportunities provided by a smart home, such as using electrical vehicles as distributed energy storage, will be considered in our future studies as well.

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