Electric Power Systems Research 111 (2014) 123–132

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Multiagent study of smart grid customers with neighborhood electricity trading

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ARTICLE INFO

Article history:
Received 20 November 2013
Received in revised form 12 February 2014
Accepted 15 February 2014
Available online 14 March 2014

Keywords:
Active customers
Agent-based modeling
Distributed demand side management
Distributed energy resources
Neighborhood electricity trading
Smart grid

ABSTRACT

The smart grid of the future may equip customers with distributed generation and storage systems that can change their overall demand behavior. Indeed, the smart grid's infrastructure provides new opportunities for the grid and its customers to exchange information regarding real-time electricity rates and demand profiles. Here we report on innovative agent-based modeling and simulation of a smart grid where active customers are modeled as self-interested, autonomous agents with their own specific load profiles and generation/storage capacities. They may choose to use locally generated power, charge/discharge their batteries, and manipulate their loads. A unique scenario for the customers analyzed for this paper is one in which customers are allowed to trade electricity within their neighborhood in order to minimize their electricity costs. Meanwhile, the grid prefers an overall uniform demand from all customers. To achieve this, we propose an effective demand flattening management scheme for the customers. A model of the active customers within the smart grid environment is used to determine the impact of the neighborhood power transactions, demand diversity, and load shifting on the customers and the utility. A number of case studies and sensitivity analyses have determined how and to what extent these parameters affect customer electricity costs and power system metrics.

1. Introduction

The electric power system is a stochastic, dynamic, and large-scale infrastructure generating electricity and accommodating different types of customers connected together through power lines. It is believed that the interconnected electric power grid of North America is one of the largest and most complex man-made machines ever built [1]. Therefore, today, a large number of tasks related to the power system, from design and planning to operation and control, cannot be accomplished without the aid of computer software and simulation-based modeling.

Recently, incorporation of new developments in data processing, system control, and communications has shifted the conventional power system toward the "smart grid" where the individual elements of a power system interact and make rational decisions in a distributed manner. This shift toward a smart grid provides an opportunity for the power system to operate more automatically with many decisions made locally rather than centrally, thus enabling better adaptivity and customization.

The discipline of multiagent systems (MASs) appears to be a promising approach to modeling such a complex system [2–20]. In general, MAS is a system of autonomous agents that interact with the environment and each other. In this paper, we describe a simulation approach to developing an MAS model of the active customer agents which can interact and make decisions within a smart grid environment. MAS-based modeling is scalable and has the ability to model stochastic and dynamic interactions among agents [21].

Multiagent systems have been used in various areas of the smart grid, including electric vehicles [2,4], load and energy management [5–10], distributed generation and storage [11–14], electricity market [15,17], and other applications [18–20]. For example, Rose et al. [5] presented a new rule-based scoring mechanism that rewards agents based on their demand estimation; but the smart grid customers are not allowed to adjust their loads at different hours and to make higher profits. Xu and colleagues [6,7] have discussed post-fault conditions where it is necessary to restore the out-of-service customers as fast as possible. They used an MAS approach from the grid's perspective toward load restoration and load shedding for an adaptive system.

Of particular interest is that smart grid customers can no longer be modeled as passive loads with limited controllability given

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http://dx.doi.org/10.1016/j.epsr.2014.02.013
0378-7796/

today's advances in smart grids and their capabilities. First, new customers' facilities may be equipped with distributed generation and storage systems, enabling the customers to supply part of their loads, store electricity for the future, and sell excess generation to the grid, all of which change the overall demand behavior from the grid's perspective. Second, a smart grid alters the way an electrical utility deals with its customers. In fact, the infrastructure of a smart grid provides new opportunities for the utility and customers to exchange information about electricity rates and electricity demand profiles. Different demand response methods have been proposed that benefit both the utility and its customers [22].

There have been several research projects on modeling smart grid customers and demand side management (DSM), most of which do not consider the active aspects of the customers in the system. Ramchurn et al. [8] modeled two general types of fixed and time-shiftable loads using a decentralized DSM approach to reducing the peak demands of consumers as well as carbon emissions. However, the Ramchurn model does not consider the customers' ability to own a distributed power generation and electricity storage system. The authors in [10] propose an efficient load management system in an electricity grid with both renewable generation and conventional power suppliers. However, customers are not able to generate or sell back electricity or to cooperate in reducing their electricity costs. Vytelingum et al. [11] propose a game theory approach to efficiently managing distributed electricity storage systems. This study shows how gradually adapting a charging strategy can lead to less fluctuations in electricity rates. Once again, customers do not have the autonomy to modify their demand based on the price signal. Finally, in [19] and [20], agent-based models of microgrids were proposed. In these studies, however, customers are modeled as electricity consumers whose ability to make autonomous decisions has not been taken into account. For the most part, these works look at the overall system without modeling the customers in detail.

It is critical to model a smart grid from the customers' perspective and then capture the consequences of their decisions on the system. We began with a basic MAS model that was previously proposed for investigating the performance of smart homes in a power system in [23]. This paper describes a major development by supporting customer agent communication and cooperation within a neighborhood for the purpose of electricity trading. The recently updated model includes industrial, commercial, and residential customer sectors with their specific demand characteristics. In addition, a new DSM method has been developed for customer electricity management as customers try to minimize their electricity costs. This method supports neighborhood power transactions and tries to alleviate the peak load through load shifting while avoiding load curtailment by efficient use of the storage system.

A number of case studies are presented and analyzed to determine the impact of smart grid features, such as neighborhood electricity trading, load shifting, load diversity, and percentage of distributed energy resource (DER) owners, on smart grid performance metrics defined from the perspective of both the customers and the electric utility. The impact of the customer agents' autonomous decisions on the smart grid are studied using sensitivity analyses which results in determining some critical variables, such as the DER capacity that leads to the minimum electricity cost for a specific customer.

The remainder of the paper is organized as follows. Section 2 introduces the smart grid modeled in this paper. Section 3 describes the design strategy of the MAS including agent diversity and other characteristics of the simulated environment. System evaluation metrics and study case parameters are provided in Sections 4 and 5, respectively. These sections are followed by the simulation results, discussion, and conclusions.

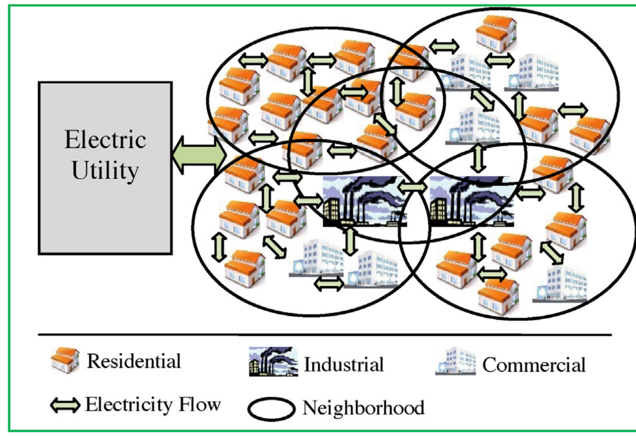

Fig. 1. Main components of the smart grid on the demand side with three customer sectors.

2. Smart grid concepts and components

The smart grid modeled is comprised of two main entities: customers and the electric utility. In addition, other components and concepts necessary to a detailed smart grid model include a renewable generation and battery system (denoted by DER in this paper) and neighborhood awareness and electricity trade, which are discussed in this section. The main idea is to incorporate the impact of neighborhood customers into the power system. Briefly, agents within a defined geographical distance are assigned to be neighbors with certain properties. A schematic of the model components is shown in Fig. 1 where bidirectional electricity flow is randomly sketched among the customers as an example. Each customer agent is capable of communicating and trading electricity both with the grid and within its neighborhood. In Fig. 1, the electric connections to the grid are represented with a single arrow, for simplicity. The components of the model are introduced as follows.

2.1. Electricity customers

Electricity customers are the key to our model. Customers can affect the smart grid by their local independent decisions. Three types of customer sectors are considered in this paper: residential, commercial, and industrial. Each customer sector has its own average load profile for a 24-hour period. In our model, the average demand of a load category at each hour of the day is put into the model and used to calculate the expected load of the corresponding customers during that hour. The loads are assumed to be normally distributed. Each customer may own a distributed power generation and electricity storage system. In addition, based on their load profiles, each customer has a demand that needs to be met by its internal resources or by purchasing the required power.

In each time step, say one hour, each customer is aware of its current demand and receives data on renewable generation, available battery capacity, and electricity rates. Customers are able to communicate with the grid and their neighbors as well. Based on the communication within the neighborhood, each customer may declare its shortage/excess of power for that hour. Then, using its demand side management program, the customer decides to take one or more of the following actions for that hour: (1) completely satisfy or shift part of the load, (2) buy electricity from the grid and/or the neighbors, (3) charge or discharge electricity in the battery storage system, or (4) sell the excess electricity generated to the grid or the neighbors and/or store it.

2.2. Electric utility

The electric utility is modeled as a single agent that provides electricity to customers and buys their excess generation based on the electricity market price. Electricity rate, denoted by the electricity purchase rate (EPR), is based on a dynamic pricing scheme that reflects the supply and demand in the system at any point in time, as described in [23]. The EPR is modeled as a function of demand, and the parameters are defined such that the change in the aggregated demand impacts the EPR. In other words, it is assumed that the number of customers in the case studies is sufficient to impact the electricity market. This aims to include the mutual impact between the customer demand and electricity rate in the smart grid. The electric grid modeled can represent load serving entities (LSEs) in the power system that provide electric service to different types of customers.

2.3. Renewable generation and storage system

We chose wind turbines as the renewable generators and batteries as the electricity storage systems. It is assumed that the renewable generators are wind turbines because of the increasing number of installations and reasonable cost in today's market [24]. The number of small wind turbines installed globally that generate power for residential customers and small business owners has increased almost 35% annually in the past few years. This incremental rate of installation is expected to be maintained in the future [25]. Other types of distributed renewable generation, such as photovoltaic (PV) systems, are also popular in today's power system and may be included in the model without loss of generality. The amount of electricity generated by each customer depends on the wind turbine capacity and wind speed. These parameters are modeled to vary for different customer sectors and from one customer to another based on a normal distribution.

In order to calculate the electricity cost of the customers described in this paper, the levelized cost of wind generation is considered, which is the overall cost of installation, operation, and maintenance over the lifetime of the wind turbine and is expressed as cents per kWh of power generation.

Considering that the availability of a renewable generation system does not necessarily coincide with the peak load, an electricity storage system is critical for effective electricity management. The primary task of this system is to store the surplus energy produced by wind generators, which can be used to supply future loads or the demands of the neighbors. The total expected cost of a battery is also considered as a levelized cost in this study.

3. Design of neighborhood interactions and demand side management

The smart grid model is designed based on the fact that the autonomous decisions made by the smart grid customers and their neighborhood interactions affect the overall system parameters, such as the total demand and electricity rate. In this regard, MAS-based implementation fits the intended type of modeling by providing a distributed analysis infrastructure with simulation features for communication and control. The customers are modeled as autonomous self-interested agents within a smart grid environment using Repast Simphony software [26], which is a flexible Java-based modeling and simulation platform for MAS studies [27].

Two design concepts are explained in the following sections: (1) the neighborhood configurations where customers can communicate and trade power before sending any request to the grid; and (2) the proposed demand side management supporting peak load alleviation and neighborhood power trade.

3.1. Neighborhood configurations

Neighboring customers are those who reside in a close geographic area. A customer agent and its connected one-hop-distant agents define the neighborhood of that agent where one-to-one communication can be established and power traded with its neighbors. In an actual power system, the communication among the local customers of a smart grid may be established through Neighborhood Area Networks [28] while the electrical power flow between neighbors is through the electric lines. Note that the size of a neighborhood is limited by a configurable parameter that limits the number of connections per agent. One-to-one connections among customer agents are randomly assigned at the start of the simulation in order to avoid biased results due to a specific configuration of the neighborhood network. The communication and control system is assumed to be completely secure and reliable. Customers from different sectors are allowed to be in the same neighborhood (Fig. 1).

When a customer agent A needs power for a specific hour, it sends a request to buy to its neighbors before directing any power demand to the grid. Any neighbor customer responding has automatically joined the trading started by customer agent A at that hour. In response to this request, each neighbor may satisfy part of the agent's demand resulting in lower subsequent demands until either customer agent A manages to fulfill its requirement or there are no other neighbors left to ask. On the other hand, when customer agent B receives a request, it replies if it has generated extra power for that hour or if it has some extra electricity stored in its battery that it does not expect to use in the near future. Every agent records the demand history of its neighboring agents which enables better estimation of future incoming requests.

In other words, agents within a neighborhood share their extra distributed energy resources. This is a win–win situation as they receive similar benefits from their neighbors when they have a need, assuming those neighbors are motivated to sell their unused energy. As a result, the overall neighborhood demand on the grid can become flatter, modifying the electricity rates to the advantage of each customer. The electricity rate traded among the neighboring customers may be the market electricity rate provided by the utility, or it may be determined based on an agreement.

3.2. Proposed demand side management program

Peak demands in the existing power system are caused by large load variations for industrial, commercial, and residential customers at different hours of a day. Residential customers, for example, are usually at work during the day; and as they return home and start using appliances and lights in the evening, the electricity demand escalates. Likewise, the peak load hours of industrial and commercial customers depend on the particular business and workload. A power system infrastructure should be designed to be capable of handling this peak load which lasts only a few hours. This results in a lot of overinvestment and inefficient asset utilization. Furthermore, power generation at high demand hours is more costly than at base load hours. Therefore, from the grid's perspective, it is desirable that the overall load profile come as close to a flat line as possible. By the same token, since electricity rates at peak demand hours are higher for consumers in a dynamic pricing scheme, customer agents prefer to better distribute—or flatten—their electricity usage throughout the day as well.

Customers owning a generation/storage system have an opportunity to reduce their peak demand by compensating for part of the load with their generated power. Considering that the availability of renewable generation does not necessarily coincide with the peak load, customers need to store the electricity generated or shift their loads in time.

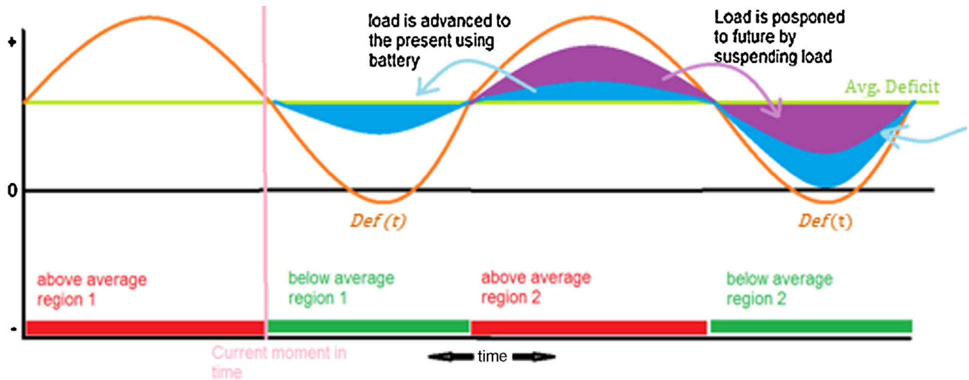

Fig. 2. Illustration of the demand-flattening scheme.

In order to consider the autonomy and privacy of the customers, the simulation model appreciates that each agent's load and generation information is obscured from the others and that the only aggregated effect of customer activities is observable via the electricity rate. On the other hand, the customers who decide to trade electricity with their neighbors are indirectly sharing information on their demands and resources which can lead to enhanced decisions. Relying solely on the electricity rate for demand management raises a new concern; because if a large group of customers decides to consume less at the current peak hour and/or shift loads, another peak load may occur at another point in time.

In this section, we propose an electricity management system based on flattening the demand and explain how it works for self-interested customer agents.

The DSM is based on customers shifting their load and using DER to alleviate their peak demand. In fact, the electricity rate exponentially increases with higher demand values. Therefore, a flatter electricity demand leads to less electricity cost for customers.

The electricity deficit at hour *j* is defined by load minus generation for that hour for each customer.

$$def(t_j) = l(t_j) - g(t_j) \tag{1}$$

Thus, a negative deficit becomes feasible when there is excess generation available. Eq. (2) calculates the mean deficit over the duration of past t_0 hours.

$$\overline{def(t_j)} = \sum_{t=t_j-t_0}^{t_j} \frac{def(t)}{t_0} \tag{2}$$

To demonstrate the proposed method, assume that the *def*(t) of a customer is as shown in Fig. 2. There are two conditions based on whether the amount of deficit at the current hour is below or over the average deficit line.

At the beginning of a below average region, the customer agent starts to increase the demand by charging the battery with a percentage of the future expected above-average deficit. As the agent enters the above average region, it can gradually discharge the battery to reduce the demand toward the average deficit. In order to smoothly distribute the tasks of charge/discharge of the battery and/or the supply of the shifted demand over the above average and below average regions, two corresponding ratios $OMR(t_j)$ and $UMR(t_j)$ are defined, respectively.

$$OMR(t_j) = \frac{def(t_j) - \overline{def(t_j)}}{\sum_{t=t_j}^{t_e} (def(t) - \overline{def(t)})}; \quad def(t_j) > \overline{def(t_j)} \tag{3}$$

$$UMR(t_j) = \frac{\overline{def(t_j)} - def(t_j)}{\sum_{t=t_j}^{t_e} (\overline{def(t)} - def(t))}; def(t_j) < \overline{def(t_j)} \tag{4}$$

where

$$t_e = E(\min(t)): \quad [t > t_j \ \ \& \ \ def(t_j) = \overline{def(t_j)}] \tag{5}$$

In the next step, if any unsupplied load is still remaining, the agent tries to postpone the shiftable part of that load ($l_{Sh}(t_j) < l_{Sh,\max}(t_j)$) to the future. Finally, for the residual demand, the agent has to buy the power from the neighbors or the grid. The customers always redirect any requests to their neighbors before asking from the grid.

Fig. 3 provides the flowchart of this method in more detail. It should also be noted that by having a lot of customer agents connected to the power system, the procedure described is a dynamic decision-making process which changes the average demand in the system. Our results for different case studies indicate that the system will eventually reach a steady state, because all autonomous agents are benefiting from lowering their demands at expensive peak hours.

4. Performance metrics

As previously described, neighborhood transactions and the electricity management program affect both the grid and customers. Therefore, two sets of performance metrics are defined to represent both perspectives.

4.1. Grid's perspective metrics

Two metrics in this paper evaluate the overall agents' performance. The first metric is the EPR, which reflects the amount of electricity demand from the grid. The second metric is the demand factor (DF), which is intended to capture the variations in the total customers' demand. This parameter is defined as the ratio of the average power demanded by all customers to the maximum total demand for the past 24 h.

$$DF(t_j) = \frac{\underset{t_j-t_0<t<t_j}{\text{mean}} \left(\sum_{i=1}^{N_C} \sum_{k=1}^{N_i} (l_{ik}(t)) \right)}{\underset{t_j-t_0<t<t_j}{\max} \left(\sum_{i=1}^{N_C} \sum_{k=1}^{N_i} (l_{ik}(t)) \right)} \tag{6}$$

where N_C is the number of load categories representing different types of customer agents; N_i and $l_{ik}(t)$ are the number of customer agents and the demand of the *k*th customer in load category *i*, respectively.

According to this definition, DF cannot be more than one; and higher values of DF mean that the customers' demands are flatter and/or more diversified in time.

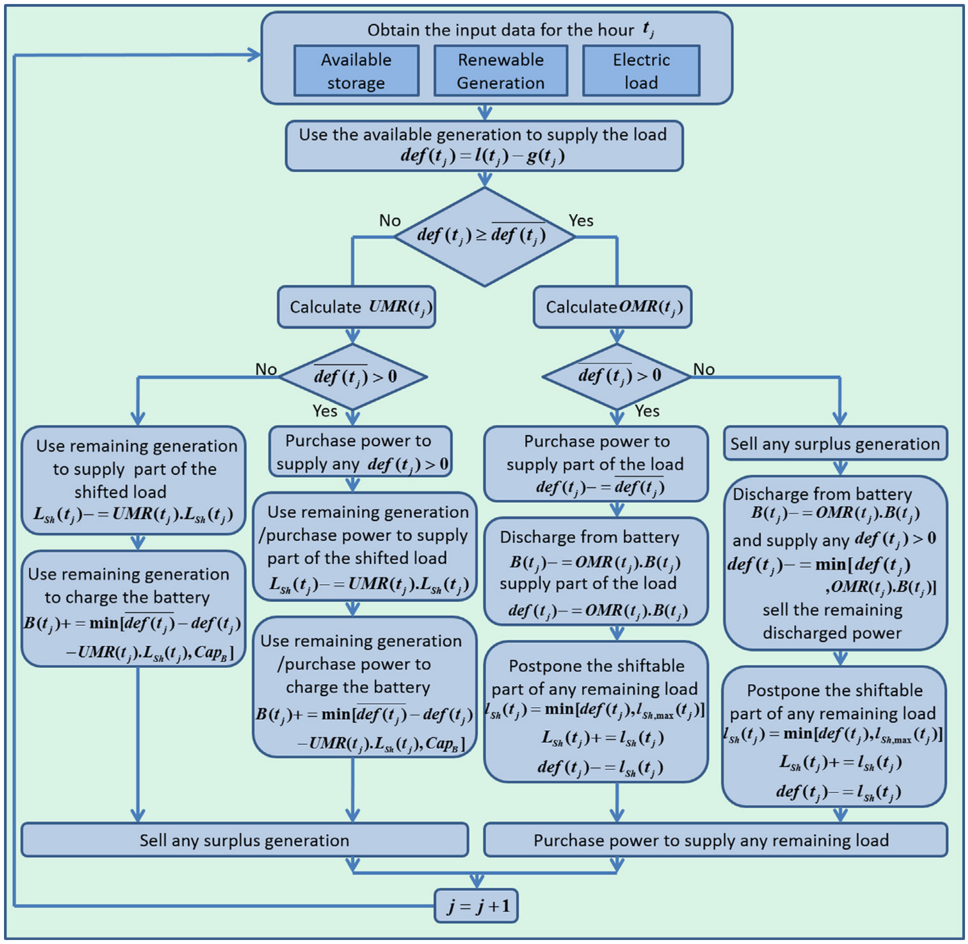

Fig. 3. Flowchart of the proposed DSM for the customers.

4.2. Customer's perspective metric

A valuable metric defined for the customers is the electricity cost of a customer (ECC) which includes the levelized costs of the battery and distributed generation per unit of time. This metric evaluates the performance of individual customers as described by (7).

$$ECC_k(t_j) = (d_k(t_j) - s_k(t_j)) \cdot EPR(t_j) + \Delta p(t_j) \cdot ER_C(t_j) + C_G \cdot Gen_k(t_j) + C_B \cdot Cap_{B_k} \quad (7)$$

where $d_k(t)$ is the kth customer's demand from the grid, and $s_k(t)$ represents the power sold to the grid by that customer. At each hour, the aggregated response of a customer is considered, which is either selling to or buying from the grid based on the DSM program. ER_C is the rate of electricity traded between the neighboring customers. $\Delta p(t)$ represents the net amount of power bought from neighbors. C_G represents the levelized cost of wind generation ($Gen_k(t)$) per kWh, and C_B is the levelized cost of battery capacity (Cap_{Bk}) per unit of time, over the expected life span. Using the levelized cost allows for study and comparison of the electricity costs for customers with and without the renewable generation and storage or evaluating a customer's cost/benefit with various capacities of renewable resources, under different operational conditions. In this study, it is assumed that the smart grid infrastructure is already in place; and, therefore, the costs associated with the implementation and design of that infrastructure have not been included in the equations.

5. Case study parameters

Different cases are studied considering three types of customers with or without generation/storage systems, load shifting, and neighborhood trading capabilities. Hourly average data used for the wind speed and customer loads was derived from [29] and [30], respectively. Table 1 provides additional information about residential, commercial, and industrial customers denoted by subscripts 1, 2, and 3, respectively. The data provided in Table 1 is referred to as the base data in sensitivity analyses of Section 6. The parameters used for calculation of the electricity rates and generation/battery costs presented in this table are based on some typical data from [31–33].

In the studies, it is assumed that the grid does not buy more electricity than its customers' total demand. Fig. 4 shows the load profile of the three load categories with a logarithmic scale. It can be observed that the peak load of a residential customer and those of commercial and industrial customers occur at different times.

6. Results and discussion

A set of cases and a number of sensitivity analyses have been performed in order to compare and contrast different scenarios (e.g., with/without neighborhood electricity transactions) and to conduct an impact analysis on various input parameters. All of the simulations have an initial transition phase which eventually leads to steady state showing the emergent behavior of the customers in the system. The steady state is determined in each study when a 90% confidence interval of a specific variable is within ±5% of its

Table 1
Parameters used for the case studies.

Parameter	N_1	N_2	N_3	$\overline{Cap_{B1}}$	$\overline{Cap_{B2}}$	$\overline{Cap_{B3}}$	$\overline{Cap_{G1}}$	$\overline{Cap_{G1}}$
Value	400	200	20	1.25	2.5	25	0.5	1
Unit	–	–	–	kWh	kWh	kWh	kW	kW

Parameter	$\overline{Cap_{G3}}$	t_0	Peak l_1	Peak l_2	Peak l_3	$\frac{EPR}{ER_C}$	C_G	C_B
Value	15	24	1	1.5	19.8	1	3.6	0.48
Unit	kW	hour	kW	kW	kW	–	Cents/kWh	Cents/kWh

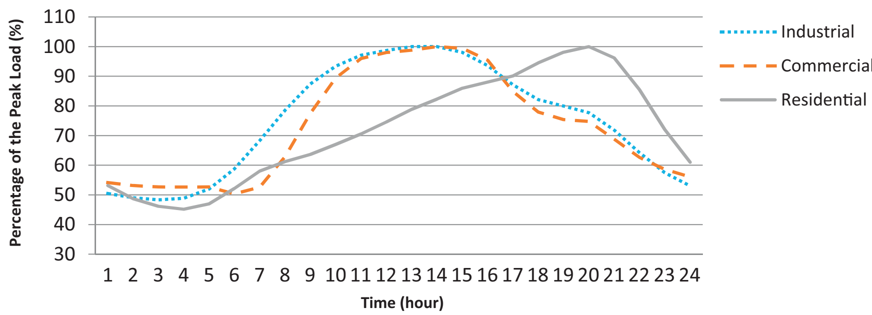

Fig. 4. Average load curve of different customer sectors.

obtained result (e.g., the electricity rate reaches the steady state in approximately1000 h of simulation). The amount of time required for a simulation to reach the steady state varies based on the type of case studies performed.

6.1. *With residential customers*

In this study, all customers are residential; and the performance of the system is evaluated under different conditions.

Fig. 5 shows the load, wind generation, and storage of an average residential customer at the steady state. We observe that peak generation does not coincide with peak load. So, the customer agents, using the proposed demand management program, make smart decisions by charging their batteries at low load hours and storing electricity to be used at the peak load time.

A sensitivity analysis on the percentage of the system's active customers (see Fig. 6) shows a decreasing trend of the mean EPR resulting from a higher percentage of the residential customers having DER in the smart grid. It indicates that proper usage of resources by the customers reduces their electricity demand both at the peak hour and on average; and, therefore, electricity rates turn out to be lower.

6.1.1. *Effects of load shifting*

This section investigates the influence of load shifting on the agents and their overall performance when all customer agents own DER. It is assumed that at each hour, a customer agent may not shift more than 10% of its load; and all of the shifted loads should be supplied back on the same day. Fig. 7 shows the transition of the electricity rates after the load shifting is activated in the simulation. The peak EPR descends as the customer agents start to shift part of their peak load, trying to avoid buying electricity at peak hours.

One interesting observation is that the minimum EPR rises after the agents start to shift their loads. The reason is that the previously shifted loads should be supplied on the same day, and the customer agents choose to buy at the minimum electricity rate and that affects the minimum EPR.

The electricity rate increases exponentially with more demand; and, therefore, shifting the load to off-peak hours reduces the individual agent's cost of electricity, as shown in Fig. 8. In this study, it is assumed that load shifting does not introduce inconvenience for the customers. If it does, that inconvenience could be included with an associated cost factor.

According to Fig. 8, customers can save on their electricity costs by owning generation-storage systems. Considering that the ECC includes the cost of DER (Eq. (7)), the results in Fig. 8 suggest that purchasing DER (in this case) is beneficial to the residential customers. In addition, they can save roughly 5–10% by shifting 10% of their loads during peak hours. It is also notable that even the conventional customers, who do not own any DER, may benefit from the lowered rates due to the presence of the DER owner customers in the system. From the grid's perspective, another valuable

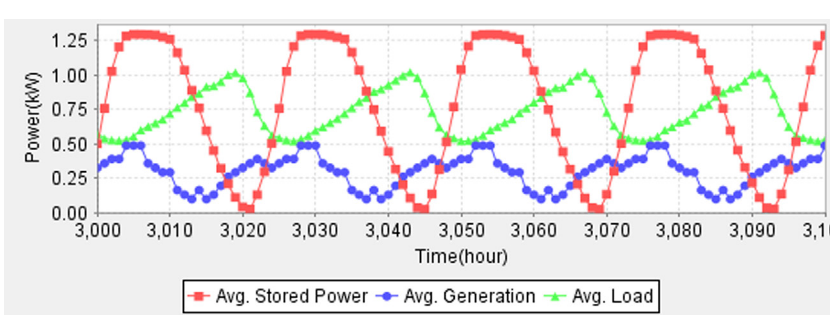

Fig. 5. Load, wind generation, and storage of an average residential customer.

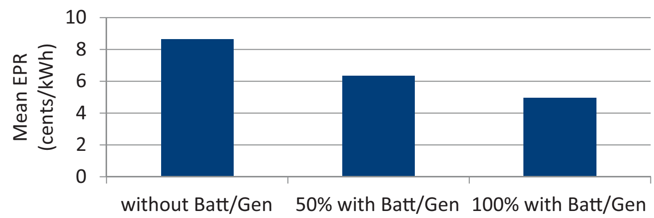

Fig. 6. Mean EPR with different percentages of residential customers owning a battery/generation system.

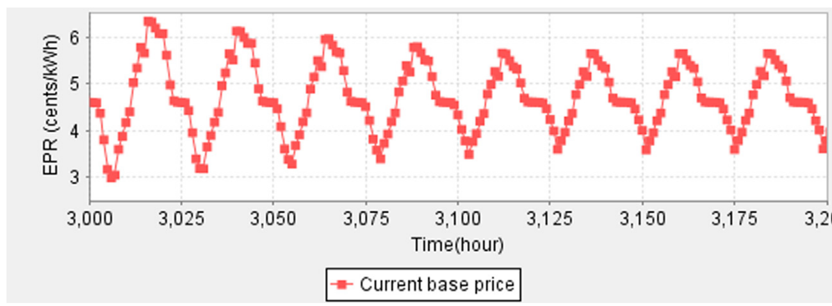

Fig. 7. The transition of the EPR influenced by customers' load shifting.

outcome of load shifting is that demand fluctuations are reduced. This can be perceived from a 12% increase in the DF based on the simulation results in this case.

6.1.2. Effects of neighborhood power transactions

To study the effects of neighborhood transactions, a new case has been simulated where half of the smart grid residential customers own DER. A sensitivity analysis was performed with different DER capacities, ranging from 1 to 4 times the base capacities of Table 1; and the results are shown in Fig. 9. As the DER capacities increase and the neighboring agents are allowed to trade power to satisfy their demands, the total demand from the grid decreases. It is also observed that electricity costs of the conventional customers who were not DER owners monotonically decreases since they benefit from lower electricity rates introduced by lower demands. On the other hand, for the DER owners, the electricity costs start to rise after a certain trade-off point; because the levelized costs of generation and storage capacities start to dominate the savings from lower electricity rates.

Therefore, according to Fig. 9, the optimum capacity size, which leads to the minimum ECC for the customers in this case, is nearly twice the base capacities provided by Table 1. What's more, the two ECC curves cross at about 1.5 $\times$ base capacities. In fact, this is the critical point of trade-off between the cost of DER and the expected savings from using them, i.e., purchasing higher DER capacities beyond this point is not economically reasonable.

Fig. 10 illustrates the transition of the electricity rates when neighborhood transactions are allowed between the customer agents. The rates are generally lower in this case, compared to Fig. 7, because the customer agents are given 4 $\times$ base capacities of DER and that reduces their demand from the grid.

Fig. 10 indicates that neighborhood power transactions can successfully shave the peak load and, accordingly, the peak electricity rate of the system. However, while the peak load is reduced, a new peak rate is observed in Fig. 10. This suggests that the neighborhood power trade cannot reduce the overall peak price considerably when the load profiles are similar. It has turned out that this new peak electricity rate corresponds to the hour with the lowest wind generation—that is, when customer agents do not have extra generation. In this case, although some battery charge may be available at the peak hour, the customers' emergent behavior is to keep the stored power for their own future load and not respond to their neighbors' requests. Therefore, the new peak in electricity rate is introduced. A solution for that would be having more diversified loads in the system.

6.2. With residential, commercial, and industrial customers

All three categories of customer agents, residential, commercial, and industrial, are included in this study. Similar to Fig. 8, electricity costs show a decreasing trend in Fig. 11, as the percentage of the customers with DER increases.

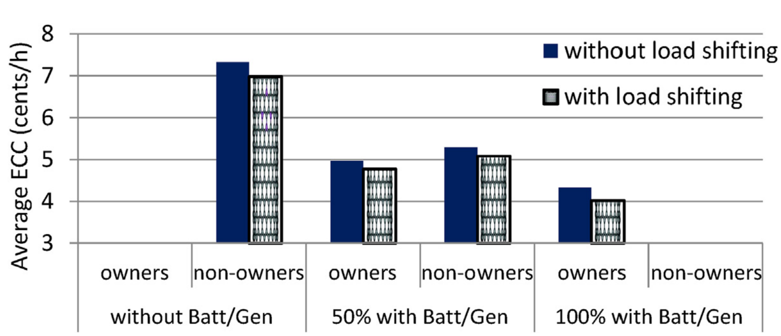

Fig. 8. Average customer's electricity cost with load shifting.

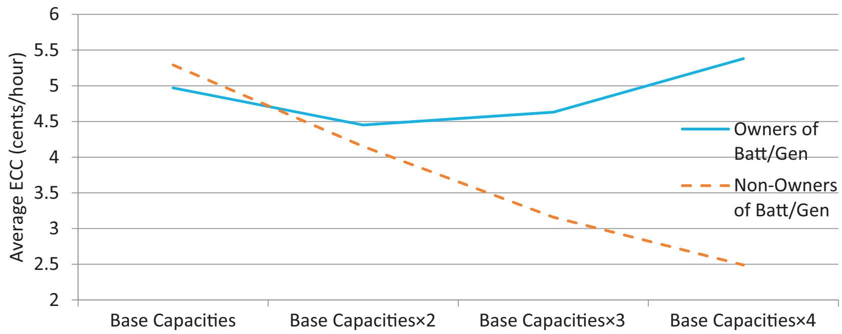

Fig. 9. Average electricity costs of customers with neighborhood electricity trade.

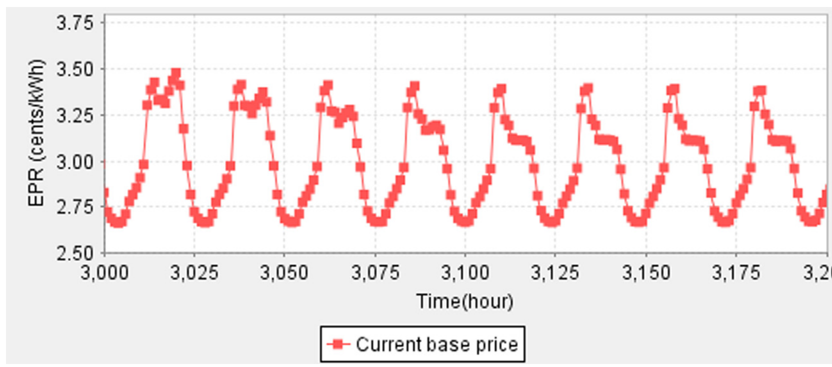

Fig. 10. The EPR influenced by neighborhood power trade.

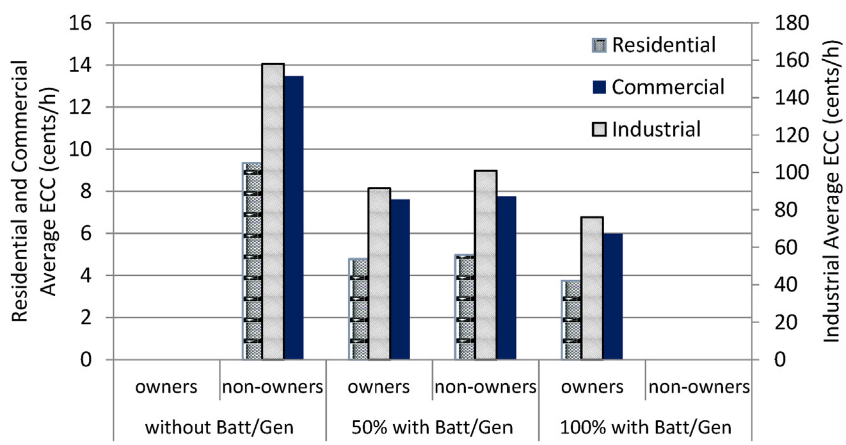

Fig. 11. Average electricity costs of customer agents of three load categories.

This figure shows that all customer agent types, even conventional customers without generation/storage systems, benefit from the increment of the distributed generation and storage in the system.

6.2.1. *Effects of load shifting*

Fig. 12 illustrates the DF with various maximum allowable load shifting. As the load shifting increases, the improvement slows down. The reason for this is that the need for shifting a higher percentage of the load arises less frequently for the customer agents, as they always try to avoid load shifting by proper usage of their generation and storage resources.

In addition, Fig. 12 provides a comparison of DF between systems with a single type and with diversified customers. According to the results, a system that includes various types of customer agents has a 2–7% higher DF and, therefore, outperforms the one

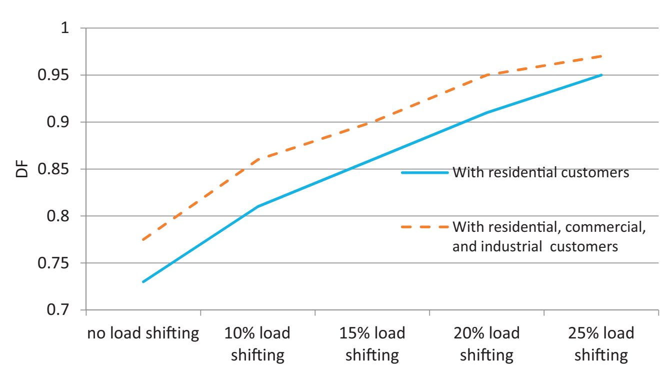

Fig. 12. Comparison of DF in two systems with different types of customer distribution.

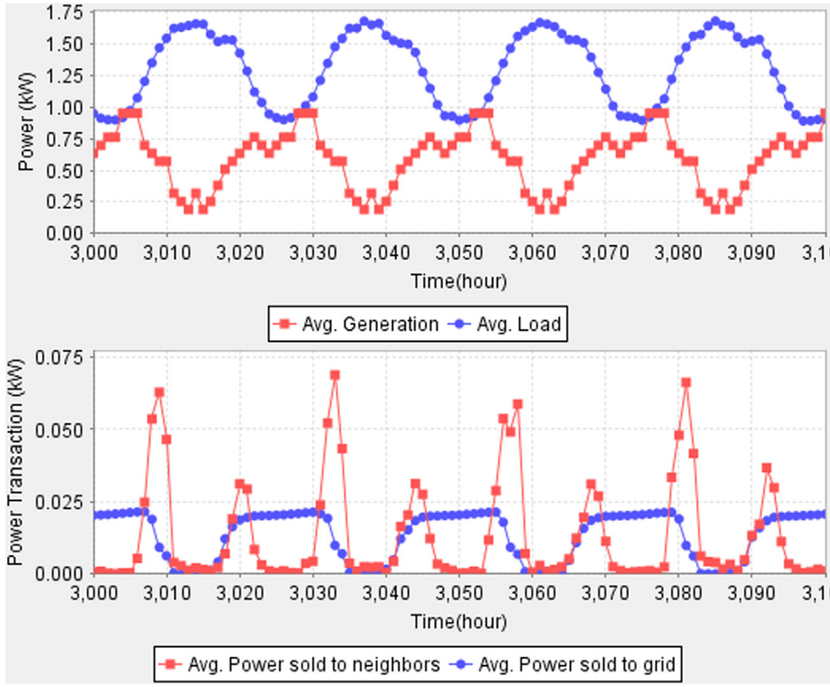

Fig. 13. Average load and generation in a system with three types of customers (top); the average power sold to the neighbors or the grid (bottom).

Table 2
Summary of the sensitivity analyses.

Features		Avg (EPR) (Cents/kWh)	Avg (ECC) (Cents/h)		
			Residential	Commercial	Industrial
Neighborhood trading not allowed	1 Customer sector	6.8	4.8	–	–
	3 Customer sectors	6.8	4.8	7.7	95
Neighborhood trading allowed	1 Customer sector	6.7	4.7	–	–
	3 Customer sectors	6.3	4.3	6.9	84
Percentage limit of load shifting	0%	6.8	4.8	7.7	95
	10%	6.4	4.2	6.7	83
	20%	6.2	4	6.4	79
Percentage of DER owners	0%	10.3	9.2	13.5	157
	50%	6.8	4.8 (5)	7.7 (7.9)	95(100)
	100%	5.1	3.9	6	78

with just one type of customer. We believe that this happens because load profiles of different customers even out and alleviate the total peak demand from the grid.

6.2.2. Effects of neighborhood power transactions

Fig. 13 shows the neighborhood transactions and the power sold back to the grid in steady state. The top graph shows the average aggregation of the demand from different categories of customers, introducing a different load profile from what was shown in Fig. 5. An average customer agent's major request of its neighbors occurs at low generation and peak load hours.

As shown in the bottom graph, the main neighborhood contributions happen at two sides of the peak load due to the lack of generation/battery at the peak hours. Neighborhood dynamic interactions are affected by stochastic parameters of the system, such as the order in which the requests are received from neighbors and the amount of the power demand. Meanwhile, each category of agents has its own times of power availability. Here, at each cycle of the day, the higher neighborhood contribution corresponds to industrial and commercial customers; and the lower contribution is associated with residential customers. For all of the other low load hours, with almost no request from the neighbors, the extra generation is sold back to the grid. As a result of neighborhood transactions in this case, the EPR decreases by 5%. The performance can be further improved by allocating more resource capacities to the customer agents.

Table 2 provides a summary of the important numerical results. According to this table, the percentage of the customers with DER has a considerable impact in reducing both the electricity cost of customers and the average electricity rate. Therefore, even the conventional customers without DER can benefit from this impact (e.g., in Table 2, notice that the ECC for conventional customers without DER, provided in parenthesis, is considerably less than in a case where none of the customers have DER). The load shifting is also an effective method of cost reduction, but the improvement slows down as the permissible percentage of load shifting increases. Neighborhood trading is beneficial especially when customers are from different load sectors. Customers of one load sector are likely to need power at the same time and not be able to help each other unless some of them own very large DER capacities.

7. Conclusions and future work

An innovative agent-based model was provided to study different types of customers and their interactions with their neighbors in a smart grid environment. The customer agents were designed to be active, i.e., to have their own electricity generation and storage system and be able to trade electricity with their neighbors. Using probability distributions, the volatility of the customers' electricity consumption, wind generation, and the grid's electricity rates were taken into account.

Moreover, considering the present and predicted future demands and renewable generation, each customer agent was motivated to minimize its cost of electricity. A customer DSM strategy was developed to properly utilize distributed generation/storage resources, shift the peak load, and trade electricity with neighbors. The model was applied to different communities of (1) uniformly residential and (2) a combination of residential, industrial, and commercial customers.

Both the customer- and the grid-side evaluation metrics were used to compare different case studies. In addition, sensitivity analyses with different percentages of customers having DER with various capacities and different load shifting capabilities provided interesting results on how these parameters impact customer electricity cost and retail electricity rates. The results indicate improved system performance with the neighborhood electricity trading feature where the effectiveness of trading among neighbors increases with more diversified customer sectors and availability of generation/storage resources. The electricity cost of customers could be reduced with neighborhood electricity trading, and there were more savings (∼10%) with diversified customers compared to similar customers (∼2%). The study showed that customers might save 5–10% with 5% of peak load shifting. In addition, customers in the power system case study could save 30% or 40% on their electricity costs if half or all of the customers purchased renewable generation and batteries and used the proposed electricity management system, respectively.

In our future work, we plan to include other restrictions imposed by an actual power grid, such as power line capacity, security, and reliability issues of communication and power systems that are critical to bidirectional power flow and neighborhood power transactions. In fact, we will study how power transactions among local customers may contribute to resolving voltage and loading issues in the system. In addition, we plan to develop and compare different DSM programs using the smart grid model presented.

References

[1] T.J. Overbye, Reengineering the Electrical Grid, American Scientist, 2000, May–June, pp. 220–229.
[2] S. Stein, E. Gerding, V. Robu, N.R. Jennings, A model-based online mechanism with pre-commitment and its application to electric vehicle charging, in: Proceedings of AAMAS, 2012.
[3] S. Vandael, N. Boucké, T. Holvoet, K. De Craemer, G. Deconinck, Decentralized coordination of plug-in hybrid vehicles for imbalance reduction in a Smart Grid, in: Proceedings of AAMAS, Taipei, Taiwan, 2011, pp. 803–810.
[4] S. Kamboj, W. Kempton, K.S. Decker, Deploying power grid-integrated electric vehicles as a multi-agent system, in: Proceedings of AAMAS, Taipei, Taiwan, 2011, pp. 13–20.
[5] H. Rose, A. Rogers, E.H. Gerding, A scoring rule-based mechanism for aggregate demand prediction in the smart grid, in: Proceedings of AAMAS, Valencia, Spain, 2012.
[6] Y. Xu, W. Liu, Novel multiagent based load restoration algorithm for microgrids, IEEE Trans. Smart Grid 2 (March (1)) (2011) 152–161.
[7] Y. Xu, W. Liu, J. Gong, Stable multi-agent-based load shedding algorithm for power systems, IEEE Trans. Power Syst. 26 (November (4)) (2011) 2006–2014.
[8] S.D. Ramchurn, P. Vytelingum, A. Rogers, N. Jennings, Agent-based control for decentralised demand side management in the smart grid, in: Proceedings of AAMAS, Taipei, 2011.
[9] R. Roche, B. Blunier, A. Miraoui, V. Hilaire, A. Koukam, Multi-agent systems for grid energy management: a short review, in: IECON 2010, Annual Conference on IEEE Industrial Electronics Society, 2010, November, pp. 3341–3346.
[10] S. Ramchurn, P. Vytelingum, A. Rogers, N.R. Jennings, Agent-based homeostatic control for green energy in the smart grid, in: ACM Transactions on Intelligent Systems and Technology, 2011, May.
[11] P. Vytelingum, T.D. Voice, S.D. Ramchurn, A. Rogers, N.R. Jennings, Agent-based micro-storage management for the smart grid, in: Proceedings of AAMAS, Toronto, 2010, pp. 39–46.
[12] G. Chalkiadakis, V. Robu, R. Kota, A. Rogers, N.R. Jennings, Cooperatives of distributed energy resources for efficient virtual power plants, in: Proceedings of AAMAS, Taipei, Taiwan, 2011, pp. 787–794.
[13] S. Miller, S.D. Ramchurn, A. Rogers, Optimal decentralised dispatch of embedded generation in the smart grid, in: Proceedings of AAMAS, Valencia, Spain, 2012.
[14] D.K. Manickavasagam, M. Nithya, K. Priya, J. Shruthi, S. Krishnan, S. Misra, S. Manikandan, Control of distributed generator and smart grid using multi-agent system, in: 1st International Conference on Electrical Energy Systems (ICEES), 2011, January, pp. 212–217.
[15] P. Vytelingum, S.D. Ramchurn, T.D. Voice, A. Rogers, N.R. Jennings, Trading agents for the smart electricity grid, in: Proceedings of AAMAS, Toronto, Canada, 2010, pp. 897–904.
[16] M. Rahimiyan, H.R. Mashhadi, An adaptive Q-learning developed for agent-based computational modeling of electricity market, IEEE Trans. Syst. Man. Cybern. C Appl. Rev. 40 (2010) 547–556.
[17] Z. Zhou, F. Zhao, J. Wang, Agent-based electricity market simulation with demand response from commercial buildings, IEEE Trans. Smart Grid 2 (December (4)) (2011) 185–194.
[18] A.A. Aquino-Lugo, R. Klump, T.J. Overbye, A control framework for the smart grid for voltage support using agent-based technologies, IEEE Trans. Smart Grid 2 (March (1)) (2011) 173–180.
[19] M. Pipattanasomporn, H. Feroze, S. Rahman, Multi-agent systems in a distributed smart grid: design and implementation, in: IEEE PSCE'09, 2009, pp. 1–8.
[20] C.M. Colson, M.H. Nehrir, R.W. Gunderson, Multi-agent microgrid power management, in: 18th IFAC World Congress, Milan, 2011, September.
[21] S. Luke, L. Panait, Cooperative multi-agent learning: the state of the art Autonomous Agents and Multi-Agent Systems, vol. 11, Springer, Hingham, MA, 2005, pp. 387–434.
[22] Rocky Mountain Institute for Southwest Energy Efficiency Project, Demand Response: An Introduction, Overview of the Programs, Technologies, and Lessons Learned, 2006, April.
[23] S. Kahrobaee, R. Rajabzadeh, L.K. Soh, S. Asgarpoor, A multiagent modeling and investigation of smart homes with power generation, storage, and trading features, IEEE Trans. Smart Grid 4 (June) (2013) 659–668.
[24] U.S. Small Wind Turbine Market Report, American Wind Energy Association, 2012, June, Available at: www.deq.mt.gov/Energy/Renewable/WindWeb/pdf/AWEASmallWindReport2011.pdf
[25] P. Zhang, Small Wind World Report Summary 2012, World Wind Energy Association (WWEA), 2012, March.
[26] Repast Website [Online] http://repast.sourceforge.net/
[27] C.M. Macal, M.J. North, Agent-based modeling and simulation, in: Winter Simulation Conference, 2009, December.
[28] G. Lopez, P.S. Moura, V. Custodio, J.I. Moreno, Modeling the neighborhood area networks of the smart grid, in: IEEE ICC 2012, Selected Areas in Communications Symposium, 2012, June, pp. 3357–3361.
[29] Historical data of hourly wind speed measured by Kimball (KIBM) airport weather station [online]. Available at: www.wunderground.com
[30] Southern California Edison Load Profiles, Regulatory Information [online], Available at: www.sce.com/wps/portal/home/regulatory/load-profiles
[31] Ameren Illinois Electricity Rate, [online], Available at: https://www2.ameren.com/RetailEnergy/realtimeprices.aspx
[32] S. Schoenung, Energy Storage Systems Cost Update, A Study for the DOE Energy Storage Systems Program, Sandia National Laboratories, SAND 2011–2730, 2011, April.
[33] K. Cory, P. Schwabe, Wind Levelized Cost of Energy: A Comparison of Technical and Financing Input Variables, Technical report, NREL/TP-6A2-46671, 2009, October.