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***Abstract*—In order to optimize energy consumption in smart grid, demand side management has gained a lot of attention recently. While existing research works attempt to optimize energy consumption either from the view point of the power company or that of users, we investigate whether it is possible to consider both parties' interests at the same time. In this paper, we propose a novel energy price model, which is a function of the total energy consumption in the considered system. In addition, a new objective function, to optimize the difference between the value and cost of energy, is proposed. The power company sends the energy price parameter and the latest consumption summary vector information to the users sequentially. Upon receiving these information, a user can optimize his own schedule and report it to the company. The company then updates its energy price parameter before communicating with the next customers. A two-step centralized game is proposed that models this interaction between the power company and its consumers. The game aims at reducing the system peak-to-average power ratio by simultaneously optimizing users' energy schedules and lowering the overall energy consumption in the system. Through simulation results the performance of the proposed game-based demand side management technique is evaluated.**

***Keywords*-Smart grid, game theory, energy usage optimization.**

I. Introduction

Recently, demand-side management [1] has received much attention from the research community since it focuses on planning and implementing electric utility activities in the smart power grid. The conventional demand-side management technique may either shift or reduce the energy consumption. Shifting the energy consumption can effectively reduce the aggregate energy load during the peak hours that may lead to power outage and load shedding events [2]. The ratio of the highest daily energy consumption to the average daily consumption, known as Peak-to-Average Ratio (PAR), can be used to measure the variation in the load-shape of daily energy consumption [3]. By applying appropriate demand-side management, it is possible to reduce the PAR by shifting the energy consumption from peak hours to off-peak ones. A different demand-side management scheme aims at mitigating the energy consumption by encouraging energy-aware consumption patterns and constructing more energy efficient buildings [4].

In our paper, we propose a new energy price model as a function of the total energy consumption. Our system considers a centralized optimization, which is more suited to the considered smart grid system. While the work in [5] served as an inspiration for applying game-theoretic technique for facilitating demand-side management, in our optimization method, we consider different objectives by modeling users' preferences about their perceived value of energy. In addition, the interactions between the power supplier and its consumers are also considered. Our adopted objective function optimizes the difference between the value and cost of energy. The power supplier pulls the customers in a round-robin fashion, and provides them with energy price parameter and current consumption summary vector. Then, each user can optimize his individual schedule and report it to the supplier. The supplier, in turn, updates its energy price parameter before it starts pulling the next consumers. This interaction between the power company and its consumers is modeled through a two-step centralized game, objective of which is to reduce the system PAR by optimizing users' energy schedules while lowering the overall energy consumption in the considered smart grid.

The remainder of this paper is structured as follows. Section II surveys relevant research work on solving the energy optimization problem in smart grid using different techniques. Section III presents our considered smart grid model and also describes our problem statement. Our optimal game-theoretic centralized algorithm is proposed in Section IV. The performance of the proposed algorithm is evaluated in Section V. Finally, Section VI concludes the paper.

II. Related Work

The analysis conducted by Wang *et al.* [6] presents case studies of dynamic pricing programs offered by electric utilities in a pilot smart grid project conducted in the United States until 2010. Smart meters were distributed to the participants of the project, and their energy consumption patterns had been studied under various dynamic pricing schemes including time of use, real-time pricing, critical peak pricing, and critical peak rebates. All smart grid customers in the project had to manually set up their schedules as per the energy price. The utility company announced new prices based on the prediction of market fluctuation and system peak load. Although the project achieved good improvement in terms of PAR reduction, it did not take into consideration how reaction from the user side could, in turn, affect (i.e., improve) these prices.

In addition, the survey and analysis in [6] also demonstrated that the biggest motivation of the participants was monetary incentive. This indicates that the attitude of the users toward the energy price is, indeed, important. Furthermore, it was suggested that the energy pricing performance could be significantly improved with the aid of automations, e.g., by having users equipped with smart thermostat to automatically reduce consumption of air conditioning and central heating during peak hours.

In [7], an optimal and automatic residential energy consumption schedule framework was introduced that is capable of forecasting the fluctuated energy price. The work is based on the idea that even though real-time pricing has several potential advantages, its benefits are currently limited due to lack of efficient automation systems in the building as well as users' difficulty in manually responding to time-varying prices. Thus, the work in [7] implied the potential of exploiting smart pricing in smart grid.

The work conducted in [4] introduced the use of utility function in an energy schedule optimization, where the energy generation capacity (during different hours) is limited. By applying the utility function, the power supplier is able to obtain the preference of users toward energy consumption and impose an appropriate price to limit the power usage. Also, a different energy pricing scheme for different users was introduced in [4]. However, this resulted in psychological unfairness amongst the customers. In order to overcome this issue, the work in [8] added load uncertainty to the pricing scheme.

In [5], Mohsenian-Rad *et al.* considered an energy consumption schedule game, which aims at reducing PAR by shifting energy use. Their approach comprises a totally distributed algorithm, as every user connects with one another and reviews their schedules. The game runs continuously so that if a user has a sudden change in his schedule, then the whole process recurred to find the equilibrium again. However, the connection between the users is not desired in smart grid and the schedule should be made beforehand, e.g., for a whole day, for which a centralized control is more suitable.

In literature, centralized optimization for scheduling energy consumption exists in [3]. The scheme in [3] relies on a social welfare function in terms of the users' preference toward energy consumption, which is the difference of the utility and cost of the energy. However, analysis on this approach is basic, particularly since it involves two quantities of different units (i.e., utility of energy and cost of energy). This work was not extended to analyze how to select appropriate utility functions and take into account monetary incentive. In contrast, a different approach was introduced in [9] that does not focus on the system improvement such as load balancing or energy consumption scheduling in smart grid. Instead, this work attempted at capturing the game (i.e., interactions) amongst different agents of smart grid, namely consumers, retailers, and the energy market. A game-based interaction with many layers is usually a complicated case. In the next section, we present our considered smart grid system model and formulate the demand-side management problem.

III. Considered System Model & Problem Statement

Fig. 1 depicts our considered hierarchical framework of the smart grid system. In this model, we consider a single energy supplier for simplicity that serves multiple consumers or users. The user-side (i.e., consumer-residence, building, and so forth) is equipped with smart meters [10]. Each smart meter is assumed to have the capability of scheduling the energy consumption of the respective consumer-residence. The smart grid users are connected with control centers. The control centers are, in turn, connected to the power company. The bi-directional communication between the control center(s) and the users is possible through these smart meters. In addition, we assume that a smart meter has the capability to monitor and collect the data of all electrical appliances of the corresponding residence that are plugged into the grid. Furthermore, the smart meters have the ability to turn on/off and select the level of energy consumption for these appliances if required. Finally, in this model, each of the deployed smart meters is capable of notifying the power company or the supplier regarding the energy consumption schedule of its respective user.

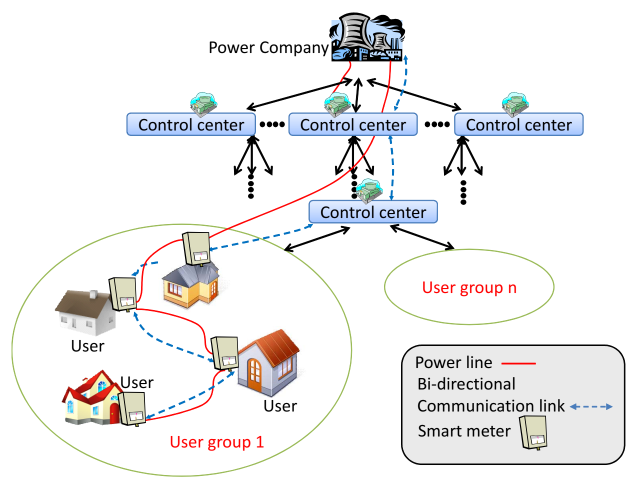

Fig. 1. Considered system architecture of the smart grid.

Indeed, the smart meters would need to determine the optimal choice of energy consumption schedule for the customers. In this vein, demand-side management, in terms of planning and implementation of the electric utility activities in the users domain, is crucial. The demand-side management in smart grid, however, has to deal with the challenging objective of shifting energy consumption.

Our objective of demand-side management, i.e., shifting energy consumption load, may effectively relieve the high aggregate energy load during the peak hours, and therefore, mitigate power outages and load shedding. The peak-to-average ratio, referred to as PAR throughout the remainder of the paper, is used to measure the imbalance in load-shape of daily energy consumption. The value of PAR is always equal to or larger than one. By shifting energy consumption from peak hours to off-peak hours, we can efficiently lower the peak load, and thus reduce PAR.

IV. Proposed Game-Theoretic Demand-Side Management Scheme

In this section, we first propose the user's and power company's strategies (for the demand-side management) respectively. Based on these strategies, we then propose a two-step game model, in which the supplier plays the role of a leader, and all the users act as its followers.

A. User's Strategy

Every user aims at maximizing his pay-off, represented by the following objective function.

$$\begin{aligned} W_i(x_1, ..., x_{24}) &= Value\ of\ Energy - Cost\ of\ Energy \\ &= V(X_i) - \textstyle\sum_{h=1}^{24} x_h C_h(L_h). \end{aligned} \tag{1}$$

where $(x_1, ..., x_{24})$ is the energy consumption scheduling vector, which contains the energy loads of that user during different hours in a day, $X_i = \sum_{h=1}^{24} x_h$ is the total energy consumption, $V(X_i)$ denotes the value of that amount of energy, L_h indicates the total energy consumption at the utility provider during the h^{th} hour, and $C_h(L_h)$ is the energy price of obtaining each unit of energy from the supplier during the h^{th} hour. Next, we describe, in detail, the two components of the user's utility function, i.e., the value and cost of energy, respectively.

1. Value of Energy, $V(X)$

$V(X_i)$ represents how much the user i values a specific amount of energy X_i. Here, we use the exponential function $(1-e^{-\omega X_i})$ as its value domain has been normalized between [0,1]. Then, we define the value function of energy as follows.

$$V(X_i) = pX_{max}(1 - e^{-\omega X_i}), \tag{2}$$

where X_{max} is the maximum amount of energy, which the user can consume. ω is a parameter representing the user's tolerance toward energy consumption curtailment. A user having a comparatively larger value of ω also has a larger value of utility even with the same amount of energy consumption. p denotes the average price for a unit of energy. This is the value of acquiring a unit of energy measured in monetary gain, regardless of other factors like time of day, additional cost for peak hours, additional cost of delivery, and so forth. The utility function we choose has a maximum value of one. It means that the user will value his consumption amount not greater than the average money he needs to pay to satisfy his maximum demand in monetary units.

2. Cost of Energy

The cost of energy for the user is based on the energy price function. Energy price will vary with real time, proportional with the system energy consumption at that hour. In this way, the consumers will have incentives to refrain from using power during peak hours, resulting in a lower load. We propose the following energy price function.

$$C_h(L_h) = \alpha L_h \log(L_h + 1). \tag{3}$$

Here, α is referred to as the price parameter. The power supplier can manipulate this parameter to change the energy price of the whole day to control energy consumption (which will be presented later).

By substituting Eqs. 2 and 3, the user i's objective function can be rewritten as:

$$\begin{aligned} W_i(x_1, ..., x_{24}) = pX_{max}&(1 - e^{-\omega \sum_{h=1}^{24} x_h}) \\ &- \sum_{h=1}^{24} \alpha x_h L_h \log(L_h + 1). \end{aligned} \tag{4}$$

B. Power Supplier's Strategy

Usally, the energy price is fixed for every unit of energy regardless time of day or total energy consumption of the system. This fixed price scheme is usually adopted in conventional power grids. For example, in case of Japan, Tokyo Electric Power Company (TEPCO) charges 17.87 yen for first 120 kW. On the other hand, the users are charged a higher price (22.86 yen) for the next 180 kW residential usage with $20A$ power line. Therefore, we assume that the supplier has this average price p for the energy, which it sells to the customers. It is worth noting that this p is the same parameter used in the user's objective function (i.e., Eq. 2). When the supplier uses the dynamic price scheme, we assume that the total cost it charges for the whole system is equal to the fixed price scheme with the same load. This can be expressed as follows.

$$\begin{aligned} p\sum_{h=1}^{24} L_h &= \sum_{h=1}^{24} L_h C_h(L_h) \\ &= \alpha \sum_{h=1}^{24} L_h^2 \log(L_h + 1). \end{aligned} \tag{5}$$

Therefore, α is equal to

$$\alpha = \frac{p\sum_{h=1}^{24} L_h}{\sum_{h=1}^{24} L_h^2 \log(L_h + 1)}. \tag{6}$$

This is our proposed strategy for the power supplier enabling the supplier to calculate the energy price parameter, denoted by α. Eventually, by using this, the power company can also generate the energy price for different hours in a day.

C. Proposed Game-Theoretic Energy Schedule (GTES) Optimization

Based on the strategies of the users and the power supplier, we now propose a two-step game model, in which the supplier acts as a leader, which directs its players, i.e., the users. In the remainder of the paper, we refer to our proposed algorithm as Game-Theoretic Energy Schedule (GTES) method. The objective of the game in GTES is system PAR reduction. The two-stages of the proposed game are as follows.

a) The users aim at maximizing their own pay-offs by optimizing their objective functions.

b) The suppliers will adjust the price of energy according to the strategies of the users.

When GTES converges to equilibrium, neither the users nor the supplier have incentives to change their strategies. As a consequence, the original objective will be fulfilled.

The stages in GTES are depicted in Fig. 2. As shown in the figure, the power supplier's control center acts as a data concentrator in GTES. The control center gathers initial information by receiving preliminary schedules from the users. Based on the initial information, the supplier then initializes the price parameter, α. Then, the power supplier pulls consumers in a round-robin fashion, and provides them with energy price parameter, α and current consumption summary vector, L_h. Each user i needs to compute his utility function W_i. It may also request for updated α and L_h from the supplier. Upon receiving the updated information, user i optimizes W_i to find the new value of X_i. This is a local optimization problem in user i's smart meter that is solved using Interior-Point-Method (IPM) [11]. The reason behind opting for this local optimization method is because of its speed and efficiency, which are important not to overwhelm the low-processing and memory resources of the smart meters. In addition, by doing so, the users do not reveal all the details about their schedules to the supplier. Instead, only the total energy consumption schedule vector is sufficient. Thus, each user optimizes his own schedule. Then, user i reports it to the supplier, which in turn updates its energy price parameter before pulling the next consumers by using Eq. 6. Thus, the users and the supplier center change their strategies, i.e., play their own games until equilibrium is achieved whereby none can improve pay-off by changing its own strategy while the others do not change theirs.

V. Performance Evaluation

In this section, we evaluate the performance of our proposed GTES approach for reducing energy consumption by comparing it with a number of conventional methods. The first conventional method is to gather all parameters and constraints from every user and schedule energy consumption by applying convex optimization to find schedule for all the users at once. For quick reference, let this approach be referred to as Centralized Convex Optimization (CCO). The second conventional method for comparison is the autonomous energy-theoretic optimization algorithm in [5] that is referred to as the Energy Consumption Game (ECG) for ease of notation. Note that while ECG is also a game-based algorithm, objective of which is to only reduce system PAR using a distributed optimization.

The simulation environment is constructed with MATLAB [12]. We consider a smart grid infrastructure with a supplier and a population of consumers. All the consumers connected to the supplier are equipped with smart meters with the assumed capability (described in Section III). The number of consumers is varied from 5 to 500. Each consumer has 10 to 15 schedulable appliances, and 10 to 15 non-schedulable appliances. The schedulable appliances include residential electrical equipment with a flexible schedule, such as washing machines, dish washers, and plug-in hybrid electric vehicles. On the other hand, non-schedulable appliances need to consume energy continuously or have a fixed schedule. Examples of non-schedulable appliances include fridge, light bulbs/lamps, and so forth. For more details about the schedulable and non-schedulable appliances, interested readers are referred to the work in [2]. While all the simulations settings are randomly generated during every simulation run, these settings remain the same for comparing the different methods in a specific situation.

First, we evaluate the running time of the compared algorithms. Fig. 3 demonstrates that the running time of CCO increases quite fast, almost at an exponential rate, while the two game-theoretic methods require significantly low completion time as the number of users increases. The large number of parameters seriously affects the running time of convex optimization (i.e., CCO), even when the number of users remains rather small. Furthermore, it can affect even the convergence guarantee. In our conducted experiment, CCO often fails to converge when the number of consumers exceeds

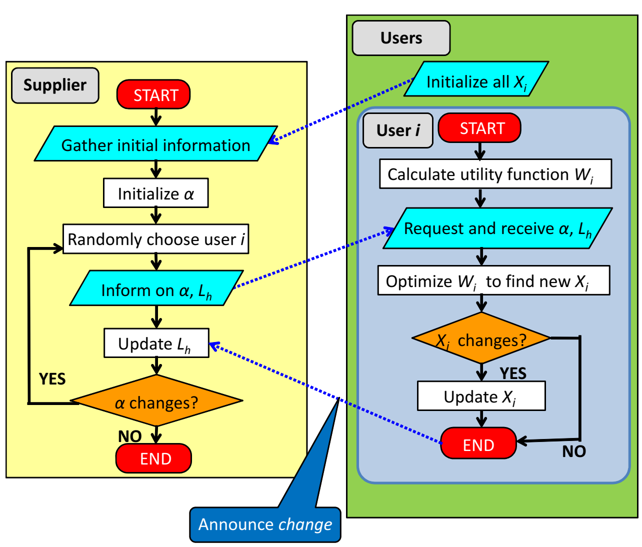

Fig. 2. Proposed Game-Theoretic Energy Schedule (GTES) algorithm.

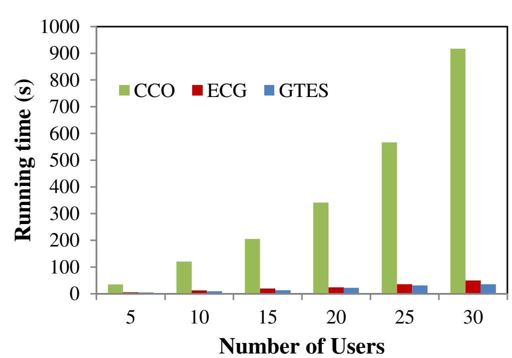

Fig. 3. Comparison of the running time among the proposed GTES, and conventional CCO and ECG algorithms for various numbers of users.

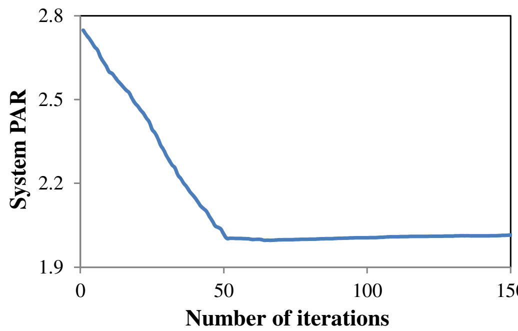

Fig. 4. Convergence of system PAR in the proposed GTES.

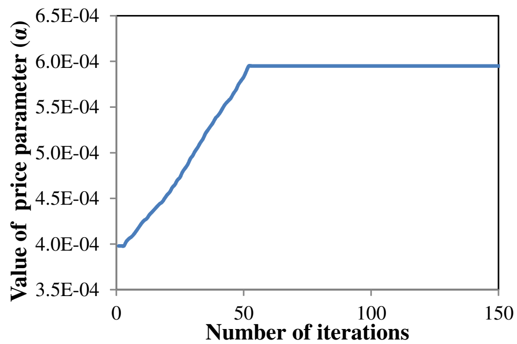

Fig. 5. Convergence of the supplier's price parameter (α) value in the proposed GTES.

30. In real life, the number of appliances for each user may be even higher, which is the reason why centralized convex optimization such as CCO may not be practical for demand-side management in smart grid. So, in the remainder of the section, we evaluate the game-based approaches only.

In Fig. 4, it is remarkable that the convergence happens significantly fast for the proposed GTES, and the system PAR drops drastically after the first round (when all the consumers had run the algorithm once). After that, the system PAR changes slowly and stabilizes after 2 to 3 rounds. This confirms that game-theoretic optimization would converge within $O(n)$ if every player (i.e., each of the consumers as well as the power company) follows the best move. Because, GTES uses IPM to solve the local problem for each user, all the users are able to find their optimal schedules, and therefore, the system approaches equilibrium state quite rapidly.

Fig. 5 demonstrates the convergence of the energy price parameter, α. As shown in the figure, this parameter convergence also happens substantially fast, similar to that on the user-side. In this way, both the games on the user-side and the supplier-end converge to equilibrium.

Fig. 6 illustrates the number of iterations needed for the convergences of ECG and the proposed GTES. Since both these methods are based on game theory, they converge very fast proportional with the number of consumers. Furthermore, as the number of consumers grows larger, the ratio between the number of iterations and the number of consumers decreases a little. This can be explained by the fact that the bigger the system becomes, the less effect is inflicted by changing a single consumer's schedule. Thus, we confirm that game-theoretic optimization approaches have high convergence speeds, and they scale well with the increase in the number of consumers.

In Fig. 7, we compare the PAR reduction between the ECG and the proposed GTES. Fig. 7 illustrates that our proposed GTES method results in higher PAR reduction in contrast with ECG. This good performance of the proposed method can be attributed to its consideration of not only shifting energy consumption while scheduling, but also its ability to adjust energy consumption levels at different hours. So, by adding more to the off-peak hours and decreasing a little at peak hours, PAR is reduced even further in GTES.

Thus, the simulation results clearly exhibit that the proposed GTES is superior to existing demand-side management techniques such as central convex optimization at the control center and distributed energy game-based approach.

VI. Conclusion

In this paper, we discussed a game-theoretic approach for optimizing energy consumption in smart grid. The objective of our work is to achieve a reduction in system PAR. We apply a real-time pricing, where energy price changes according to

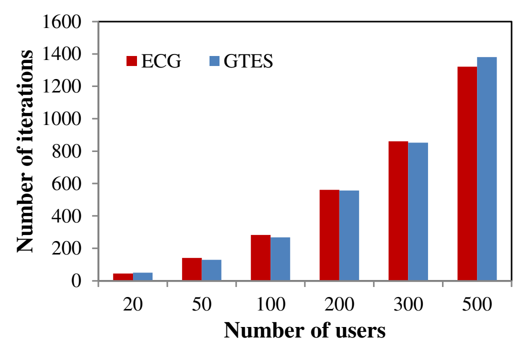

Fig. 6. Number of iterations required for ECG and the proposed GTES for a large number of users (up to 500).

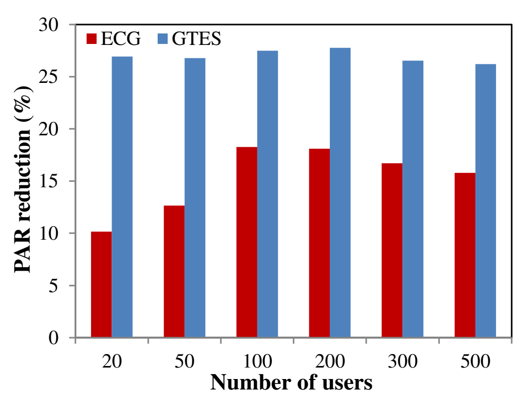

Fig. 7. PAR reduction in ECG and the proposed GTES for different numbers of users.

the whole system energy consumption during each hour, so that all the participants have incentive to follow the program. Our conducted simulations demonstrate that the proposed algorithm converges within a reasonable number of iterations, achieves considerable amount of PAR reduction, and exhibits scalability to increasing number of users.

ACKNOWLEDGMENT

The work of Ivan Stojmenovic was also supported by the Government of China for the Tsinghua 1000 Plan Distinguished Professor (2012-5) position.

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