Bargaining-Based Smart Grid Pricing Model for Demand Side Management Scheduling

Youngjae Park and Sungwook Kim

A smart grid is a modernized electrical grid that uses information about the behaviors of suppliers and consumers in an automated fashion to improve the efficiency, reliability, economics, and sustainability of the production and distribution of electricity. In the operation of a smart grid, demand side management (DSM) plays an important role in allowing customers to make informed decisions regarding their energy consumption. In addition, it helps energy providers reduce peak load demand and reshapes the load profile. In this paper, we propose a new DSM scheduling scheme that makes use of the day-ahead pricing strategy. Based on the Rubinstein–Stahl bargaining model, our pricing strategy allows consumers to make informed decisions regarding their power consumption, while reducing the peak-to-average ratio. With a simulation study, it is demonstrated that the proposed scheme can increase the sustainability of a smart grid and reduce overall operational costs.

Keywords: Demand side management, game theory, Rubinstein–Stahl bargaining model, smart grid, two-sided price control.

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I. Introduction

According to the U.S. Department of Energy report, the demand and consumption for electricity in the U.S. have increased by 2.5% annually over the last 20 years [1].

In a traditional electrical power grid, the flow of information between provider and consumer is usually unidirectional; that is, the provider controls the flow of information. To overcome this limitation, smart grid (SG) technology is expected to revolutionize the way that electric energy is produced and distributed through the power grid [2]. In SG infrastructures, a new technique alled demand side management (DSM) was introduced to ensure a more efficient use of any available energy. DSM is a scheduling function designed to control levels of consumer energy consumption. It allows consumers to make informed decisions regarding their energy consumption, and it helps the power providers reduce the peak-to-average ratio (PAR) of energy consumption. Therefore, an SG system adaptively reshapes the consumer power demand profile [2]–[4]. If we wish to implement DSM in an SG, then we should consider the important role that day-ahead pricing plays, since any such pricing strategy can greatly influence consumers power consumption patterns [5]. Moreover, most existing price-strategy approaches for SGs in the current literature are not suitable to be practically implemented in real-world operations.

Nowadays, game theory has become a powerful tool to analyze and improve the performance of mathematically based protocols. Therefore, game theory is a suitable tool for the study of how a power supplier may interact with its consumers and how, in turn, they may cooperate with each other in an SG. As such a study is an example of a cooperative game, the Rubinstein–Stahl bargaining model can be used to develop a suitable incentive mechanism, which is needed for the cooperation of consumers and suppliers [5]–[7].

In this paper, we propose a new price-based DSM scheme that is centered on the Rubinstein–Stahl bargaining model. By adopting a two-sided dynamic pricing strategy, a power supplier and its consumers iteratively change their respective current strategies (power load profile) and repeatedly interact with other. For example, a power supplier can encourage its consumers to schedule their power consumption profile in accordance with its pricing policy. For consumers to minimize their respective electricity bills, they should adaptively respond to the energy prices set by their supplier [8]. The dynamics of such an interactive feedback mechanism means that there is the potential for a cascade of interactions between supplier and consumers to quickly find the most profitable price. In light of this fact, an important feature of the proposed scheme is that it adopts a bargaining-based cooperative pricing approach, which is implemented using the players' patience factors.

Some researchers considered the use of the Stackelberg game model in the management of an SG. In this model, the electricity retailer, as the Stackelberg leader, makes decisions on which electricity sources to procure electricity from, how much electricity to procure, and the optimal retail price to offer to its customers, to maximize its profit [9]. The customers, who are the followers in the Stackelberg game, adjust their individual electricity demand to maximize their individual utility. Even though the Stackelberg game model can capture the sequential dependence of the decisions, there are some disadvantages. First, competition among retailers cannot be added. Second, situations where only partial information on customers' utility and preferences is obtained, were not considered. In this situation, the system needs to be modeled as a dynamic game with incomplete information. Third, the traditional Stackelberg game should be elaborated by using more adaptable economic models, such as screening and signaling models [9].

Recently, several SG management schemes, such as day-ahead pricing with scheduling flexibility (DPSF) [5] and game-theoretic energy consumption scheduling (GECS) [4], have been presented for SG systems. All the earlier work in such schemes has attracted a lot of attention, and the authors of these works introduced unique challenges in their attempts to efficiently solve the problem of DSM in SGs. Compared to the aforementioned schemes, the proposed scheme attains better performance.

II. Proposed Dynamic Control Algorithms for SG Management

In this section, the proposed scheme is explained in detail. We present a generalized day-ahead DSM strategy for future SGs. The main objective of our scheme is to maximize economic benefit by reducing the peak load demand.

1. Basic Model for SG System

In this work, we assume that the SG system provides power to a set of power consumers. We denote this set as $\mathcal{N}$, such that $\mathcal{N} = \{1, \ldots, N\}$, where N is the maximum number of power consumers. Each consumer is equipped with a smart meter, which can automatically schedule the energy consumption. The smart meters are all connected to the power line coming from the power provider. Suppose there are T periods in a day; for example, $T = 24$. Then, without loss of generality, time granularity is one hour. For each consumer $(n \in \mathcal{N})$, $\mathbb{A}_n$ is defined as the set of consumer n's appliances. Thus, for any given appliance a, we have $a \in \mathbb{A}_n$. In addition, $v_{n,a}^t$ is appliance a's power consumption at time t, which can be scheduled. Therefore, a power consumption–scheduling vector of appliance a can be denoted by $\mathbf{v}_{n,a}$ = $[v_{n,a}^1, v_{n,a}^2, \ldots, v_{n,a}^T]$, and q_n^t is defined as the total power load at time $t \in \mathcal{T} = \{1, \ldots, T\}$.

$$q_n^t = \sum\nolimits_{a \in \mathbb{A}_n} v_{n,a}^t \quad \text{s.t.} \quad q_n^{\min} \le q_n^t \le q_n^{\max}, \tag{1}$$

where $q_n^{\max}$ and $q_n^{\min}$ are the maximum and minimum power consumptions of consumer n; that is, we assume for $q_n^{\min}$ that all appliances belonging to consumer n are in system standby mode, and vice versa for $q_n^{\max}$. The daily power load for consumer n is denoted by $\mathbf{q}_n = \left[q_n^1, q_n^2, \ldots, q_n^T\right]$, and the sum of the total load of customers at any given time t can be calculated as

$$Q^t = \sum\nolimits_{n=1}^{N} q_n^t. \tag{2}$$

The main goal of the power supplier is to reduce the PAR by shifting the power consumption from peak periods to off-peak periods. From the consumer's point of view, the price of the power is the main interest; the higher the PAR, the higher the power price. Therefore, reducing the PAR is the major objective for consumers. Considering the requirements of both sides, our scheduling scheme is designed to minimize the PAR. Traditionally, the PAR is given by

$$\text{PAR} = \frac{\max_{t \in T}\left(\sum\nolimits_{n \in N} q_n^t\right)}{\frac{1}{T} \times \sum\nolimits_{n=1}^{N} \sum\nolimits_{t=0}^{T} (q_n^t)}. \tag{3}$$

Based on the set of power consumption–scheduling vectors $(v_{n,1}, \ldots, v_{n,a})$, v_n denotes customer n's total energy consumption–scheduling vector $\mathrm{v}_n = [v_{n,1}, v_{n,2}, \ldots, v_{n,a}]$, for all appliances, where $\mathbf{v}_{n,1} = [v_{n,1}^1, v_{n,1}^2, \ldots, v_{n,1}^T]$. Finally, the proposed scheme can be characterized by the following problem:

$$\min_{\mathbf{v}_n} \max_{t \in \mathcal{T}} \left(\sum_{n \in N} q_n^t\right). \tag{4}$$

In an SG system, there are two main prices to consider: the consumer's expecting price, p^{t_d}, and the supplier's expecting price, p^{t_s}. The consumer's expected price (p^{t_d}) can be adjusted according to the shifting load ratio. In our scheduling model, x_n^t is defined as the shifted total power load, which is the variation within the time period *t*. Therefore, within the time period *t*, the power load decreases. By considering the shifting load ratio, x_n^t / q_n^t, $p_n^{t_\mathrm{d}}$ can be defined as follows:

$$p_n^{t_\mathrm{d}} = p^{t_0} \times \left\{1 + \left(\frac{x_n^t}{q_n^t}\right)\right\} \text{ s.t. } p^{t_0} = \frac{\left(\sum_{n=1}^{N} q_n^t\right)^{\psi}}{\sum_{n=1}^{N} q_n^t}, \tag{5}$$

where p^{t_0} is the initial retail price obtained by the general law of supply and demand; it is decided to be proportional to the supplier's generation cost [1]. The variable ψ is a control parameter for the cost function. For energy efficiency, q_n^t is preferred to have the same value as the average power load (Q_{avg}) in the time period *t*. Therefore, the supplier's expecting price (p^{t_s}) increases when q_n^t and Q_{avg} become estranged from each other. Based on this assumption, the supplier's expecting price (p^{t_s}) can be defined as follows:

$$p^{t_\mathrm{s}} = p^{t_0} \times \left\{1 + \left|\frac{\sum_{n=1}^{N} q_n^t - Q_{\mathrm{avg}}}{\sum_{n=1}^{N} q_n^t}\right|\right\} \text{ s.t. } Q_{\mathrm{avg}} = \frac{\sum_{t=1}^{T}\sum_{n=1}^{N} q_n^t}{T}. \tag{6}$$

In our model, the retail price (p^t) for time *t* is determined as the weighted sum of p^{t_s} and p^{t_d}.

$$p^t = \omega \times p^{t_\mathrm{s}} + (1-\omega) \times p^{t_\mathrm{d}}, \tag{7}$$

where ω is a weighted factor in the prices of both sides. In the proposed scheme, the basic concept of the Rubinstein–Stahl bargaining method is adopted to adjust the ω value.

2. Rubinstein–Stahl Bargaining Model

In 1982, the Rubinstein–Stahl bargaining model was proposed as a solution to problems involving two players who are bargaining over the division of a given benefit [10]. Players negotiate with each other by alternately proposing counter offers. After several rounds of offers and counter offers, players finally come to an agreement. In the Rubinstein–Stahl bargaining model, there exists a unique solution for this kind of bargaining process [9]. We assume that the Rubinstein–Stahl bargaining model's equilibrium point is obtained according to the supplier's offer (x_s^*) and consumer's offer (x_d^*). A supplier, in making an offer (x_s^*), realizes that consumers could reject it, and a consumer may then make a counter offer (x_d^*) in the next time period. If both supplier and consumer follow their equilibrium offers, then their offers would be accepted. Therefore, we can model how a consumer's rejection would decrease a supplier's payoff by the following equation:

$$1 - x_\mathrm{s}^* = \delta_\mathrm{d} \times x_\mathrm{d}^*. \tag{8}$$

A supplier can entice a consumer into accepting their offer by making it generous enough so as to give the consumer an amount that is equal or similar to their expecting payoff. In a manner similar to the above, a consumer can come to realize that their supplier may reject their counter offer, and their supplier may make a counter offer (x_s^*) in the next period. Thus, similarly, we can model how a supplier's rejection would decrease a consumer's payoff by the following equation:

$$1 - x_\mathrm{d}^* = \delta_\mathrm{s} \times x_\mathrm{s}^*. \tag{9}$$

Solving these two equations, we obtain the following:

$$x_\mathrm{s}^* = \frac{1-\delta_\mathrm{d}}{1-\delta_\mathrm{s}\delta_\mathrm{d}} \quad \text{and} \quad x_\mathrm{d}^* = \frac{\delta_\mathrm{d}(1-\delta_\mathrm{s})}{1-\delta_\mathrm{s}\delta_\mathrm{d}}. \tag{10}$$

Finally, we can find out the equilibrium point according to (10). Based on the concept of equilibrium, this final agreement in the Rubinstein–Stahl model can be expressed as follows:

$$\begin{gathered}\left(x_\mathrm{s}^*, x_\mathrm{d}^*\right) = \left(\frac{1-\delta_\mathrm{d}}{1-\delta_\mathrm{s}\delta_\mathrm{d}}, \frac{\delta_\mathrm{d}(1-\delta_\mathrm{s})}{1-\delta_\mathrm{s}\delta_\mathrm{d}}\right) \\ \text{s.t. } \left(x_\mathrm{s}^*, x_\mathrm{d}^*\right) \in \boldsymbol{R}^2 : x_\mathrm{s}^* + x_\mathrm{d}^* = 1, \\ x_\mathrm{s}^* \geq 0,\ x_\mathrm{d}^* \geq 0, \text{ and } 0 \leq \delta_\mathrm{d},\ \delta_\mathrm{s} \leq 1.\end{gathered} \tag{11}$$

Let δ_d and δ_s be the respective consumer and supplier patience factors. The more patience one has, the more payoff one attains. By this, we mean that if consumers know the current price of electricity at the earliest possible moment, then they may make use of their time and resources to plan an effective power consumption schedule for themselves; thus, with this knowledge in hand, they would then be able to exercise a certain level of patience to obtain the most profitable price. However, in this context, it is usually the supplier that has the greater level of patience. Consequently, we can represent the consumer's patience as a monotonic time decreasing function [9] as follows:

$$\begin{gathered}\delta_\mathrm{d}(r) = 1 - \frac{e^{\pi^r} - e^{-\pi^r}}{e^{\pi^r} + e^{-\pi^r}} \quad \text{s.t. } \frac{\mathrm{d}\delta_\mathrm{d}(r)}{\mathrm{d}r} < 0, \\ \delta_\mathrm{d}(0) = 1, \text{ and } \delta_\mathrm{d}(\infty) = 0,\end{gathered} \tag{12}$$

where π is the patience coefficient, and *r* represents the *r*th round of the bargaining process. According to the market-based economic model, the payoff of the power supplier is related to the payments of consumers. In this context, the longer the bargaining process goes on, the less opportunities there are for consumers to take control of their power demand; thus, they end up paying more. Based on this consideration, we adopt the following equation for the supplier's patience [9]:

$$\delta_{\mathrm{s}}(r) = \frac{e^{\pi^r} - e^{-\pi^r}}{e^{\pi^r} + e^{-\pi^r}} \quad \text{s.t.} \quad \frac{\mathrm{d}\delta_{\mathrm{s}}(r)}{\mathrm{d}r} > 0, \qquad (13)$$
$$\delta_{\mathrm{s}}(0) = 0, \text{ and } \delta_{\mathrm{d}}(\infty) = 1,$$

In (12) and (13), the patience coefficient (π^r) affects the patience factor of both sides. For an ideal management of SG, the average energy demand (Q_{avg}) and the total energy demand are expected to be identical. To reach this ideal situation, we dynamically adjust the value of π. In this work, π^r can be defined as follows:

$$\pi^r = 1 - \frac{Q_{\mathrm{avg}} - \left(\sum_{n=1}^{N} q_n^t\right)}{\sum_{n=1}^{N} q_n^t} \quad \text{s.t. } \pi^r < 2. \qquad (14)$$

By altering the value of π^r, consumers can be encouraged to schedule their current power consumption to approximate the Q_{avg}. Therefore, we can obtain the weighted factor in equation (7) in terms of (12) as follows:

$$\omega = \frac{1-\delta_{\mathrm{d}}}{1-\delta_{\mathrm{s}}\delta_{\mathrm{d}}} \text{ and } (1-\omega) = \frac{\delta_{\mathrm{d}}(1-\delta_{\mathrm{s}})}{1-\delta_{\mathrm{s}}\delta_{\mathrm{d}}}. \qquad (15)$$

Finally, we can get the retail price vector ($\mathcal{P} = [p^1, p^2, \ldots, p^t]$) in accordance with equations (7) and (15). When the price p^t is received from the power supplier, each consumer can then estimate their own payoff ($U_i(\mathbf{v}_n)$). The consumers aim to maximize their individual payoffs.

$$\max_{\mathbf{v}_n} U_i(\mathbf{v}_n) = \max_{\mathbf{v}_n}\left(-\sum_{t=1}^{T} p^t \times q_n^t\right), \quad \text{s.t. } i \in N. \qquad (16)$$

Each consumer individually solves the above optimization problem in a distributed manner, and the solution ($\mathbf{v}_n$) is obtained. Then, $\mathbf{v}_n$ becomes the input value in the power supplier's optimization problem. To achieve a better profit than before, the power supplier determines how to adjust the price vector while examining the payoff periodically. In Fig. 1, the main steps of the proposed scheme are shown and are explained in more detail in the following:

- Step 1. At the initial stage, each consumer's smart meter calculates an initial consumption vector, and the supplier then calculates initial price $\mathcal{P}$.
- Step 2. The supplier broadcasts $\mathcal{P}$ to all consumers, and all consumers can then obtain the initial $\mathcal{P}$ from their power supplier.

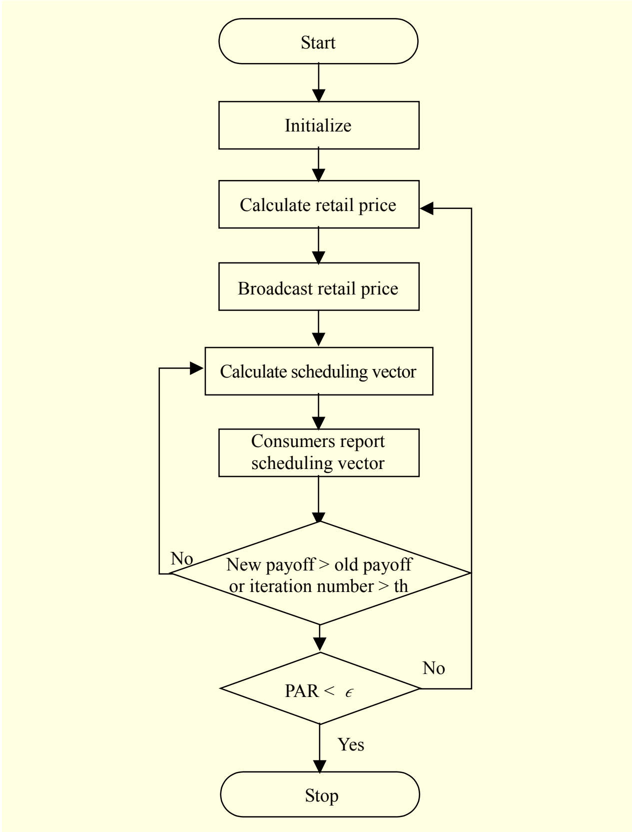

Fig. 1. Flow chart of algorithm.

- Step 3. Consumers report their respective consumption vectors, which are revised by their smart meters, and prices $p^{t_{\mathrm{d}}}$ to their respective power supplier. The power supplier is then able to obtain $p^{t_{\mathrm{s}}}$, $p^{t_{\mathrm{d}}}$, and ω by using (7) and (15). Then, the power supplier calculates $\mathcal{P}$.
- Step 4. Consumers compare their old consumption vector's payoff with their new consumption vector's payoff. If the new consumption vector's payoff is better, then go to the next step. Otherwise, go back to step 3.
- Step 5. If the PAR is lower than ϵ, then the algorithm terminates. Otherwise, go back to step 2.

Figure 1 shows the proposed interactive feedback process. This interactive feedback process continues until system convergence is obtained.

III. Performance Evaluation

In this section, the effectiveness of the proposed scheme is validated through simulation. To emulate a real-world SG environment and for a fair comparison, we consider the system parameters and power consumption as outlined in Table 1 and Table 2, respectively. Using a simulation model, the performance of the proposed scheme is compared with the two existing SG management schemes; the DPSF scheme [5] and

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Table 1. System parameters.

Parameter	Value
Number of consumer (N)	10
Number of consumer n's appliance ($\mathbb{A}_n$)	40
Number of shiftable appliance (Max)	15
Number of shiftable appliance (Min)	5
Number of non-shiftable appliance (Max)	35
Number of non-shiftable appliance (Min)	25
Maximum power consumption for each consumer ($q_n^{\max}$)	10.5 kWh
Minimum power consumption for each consumer ($q_n^{\min}$)	0 kWh
ψ value	$\psi = 2$
T value	$T = 48$
Threshold value of convergence	$\varepsilon = 1.5$

Table 2. Power consumption.

Time (hour)	1	2	3	4	5	6
Consumption (kW/h)	376	210	98	189	189	189
Time (hour)	7	8	9	10	11	12
Consumption (kW/h)	309	376	330	309	309	995
Time (hour)	13	14	15	16	17	18
Consumption (kW/h)	376	538	520	538	651	816
Time (hour)	19	20	21	22	23	24
Consumption (kW/h)	1,321	1,321	995	1,138	651	376
Time (hour)	25	26	27	28	29	30
Consumption (kW/h)	376	210	98	189	189	189
Time (hour)	31	32	33	34	35	36
Consumption (kW/h)	309	376	330	309	309	995
Time (hour)	37	38	39	40	41	42
Consumption (kW/h)	376	538	520	538	651	816
Time (hour)	43	44	45	46	47	48
Consumption (kW/h)	1,321	1,321	995	1,138	651	376

the GECS scheme [4].

The performance of the SG usually depends on the power consumption, power cost, and payment that is paid by all consumers. In this paper, the performance measures obtained through simulation are the consumer's power consumption and the normalized payment.

In Fig. 2, the consumers' power demand profiles are compared over 48 time periods. From the simulation results, we can see that the consumers' demand profiles under the proposed scheme have a flatter power consumption than those under the other existing schemes. At the same time, our

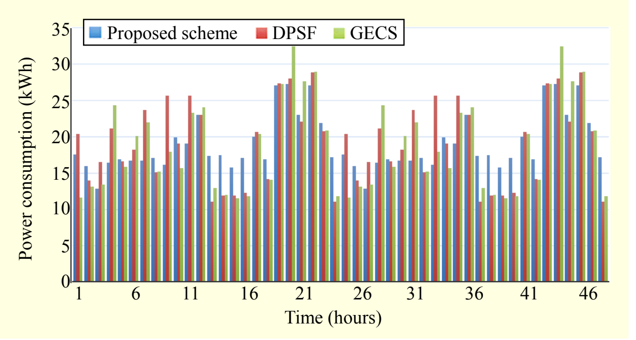

Fig. 2. Power consumption.

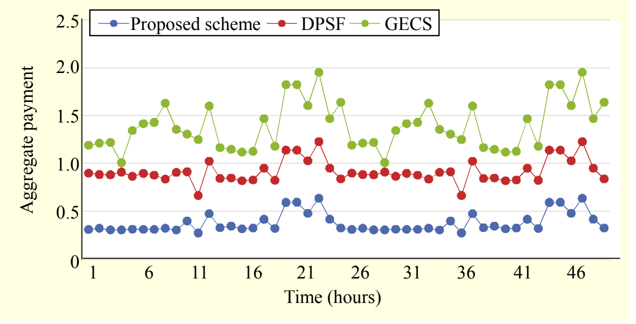

Fig. 3. Aggregate price comparison.

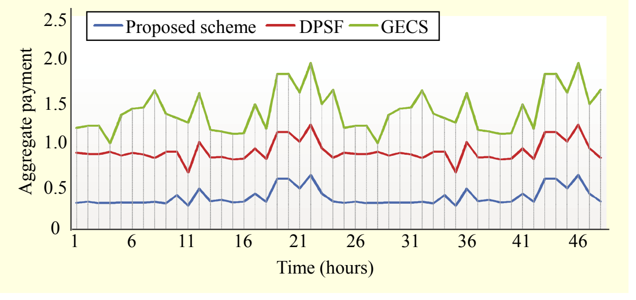

Fig. 4. Aggregate payment comparison.

proposed scheme can reduce the peak demand further than the other schemes by using a dynamic scheduling technique.

Figure 3 shows the aggregate price comparison for the three schemes. In this work, the "aggregate price" is the multiplication of power consumption demand and price rate. These performance criteria represent consumers' profits; our scheme can be obtained by effective power consumption scheduling. We can see that the consumers' payments in the proposed scheme are less than those in the other existing schemes.

Figure 4 shows the hourly aggregate payment required of all consumers. Usually, a lower PAR value means that suppliers can reduce their costs. From a supplier's point of view, our scheme can effectively decrease PAR, which is a critical factor in deciding the cost of power. Therefore, in the proposed scheme, consumers tend to have a significantly lower hourly aggregate payment than in other schemes, which in the end, is of more benefit to the supplier. Therefore, we claim that our proposed approach can improve the efficiency of an SG system. From the simulation results in Figs. 2–4, it can be seen that the proposed scheme, in general, performs better than the existing schemes. Based on an adaptive, interactive learning approach, the proposed scheme can constantly monitor SG conditions and appropriately balance the system performance, whereas the other schemes ([4] and [5]) cannot offer such an attractive system performance.

IV. Summary and Conclusion

Recently, the design of effective SG management algorithms has been the subject of intense research. In particular, the day-ahead pricing DSM approach is widely used to dynamically change or shift the electricity consumption of consumers. In this paper, we proposed a new two-sided pricing algorithm for future SG systems. For practical SG operations, the proposed game-based algorithms are designed in a self-organizing, dynamically interactive and distributed fashion. The dynamics of our interactive feedback game model can cause a cascade of interactions between supplier and consumers to effectively find the most profitable price for both parties. Unlike other existing SG control schemes that require the exchanges of messages between consumers, the proposed pricing scheme requires only interactions between a power supplier and its consumers via pricing information. This distributed simple approach is highly desirable for real-world system operations. Simulation results confirmed that our scheme can provide better benefits, not only for the energy provider but also for the consumers. For future study, we will consider the SG security issue (that is, the effect of malicious consumers).

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