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A Game-Theoretical Scheme in the Smart Grid With Demand-Side Management: Towards a Smart Cyber-Physical Power Infrastructure

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ABSTRACT The smart grid is becoming one of the fundamental cyber-physical systems due to the employment of information and communication technology. In the smart grid, demand-side management (DSM) based on real-time pricing is an important mechanism for improving the reliability of the grid. Electricity retailers in the smart grid can procure electricity from various supply sources, and then sell it to the customers. Therefore, it is critical for retailers to make effective procurement and price decisions. In this paper, we propose a novel game-theoretical decision-making scheme for electricity retailers in the smart grid using real-time pricing DSM. We model and analyze the interactions between the retailer and electricity customers as a four-stage Stackelberg game. In the first three stages, 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 the customers, to maximize its profit. In the fourth stage, the customers, who are the followers in the Stackelberg game, adjust their individual electricity demand to maximize their individual utility. Simulation results show that the retailer and customers can achieve a higher profit and higher utility using our proposed decision-making scheme. We also analyze how the system parameters affect the procurement and price decisions in the proposed decision-making scheme.

INDEX TERMS Cyber-physical systems, smart grid, demand-side management, real-time pricing.

I. INTRODUCTION

As a critical infrastructure, the electricity power grid forms one of the largest complex interconnected networks. The current power grid is managed through an old-fashioned centralized cyber-infrastructure, referred to as supervisory control and data acquisition (SCADA) [1]. A failure in one location can quickly propagate across the grid, and can also lead to a cascading failure and wide-spread blackouts, such as the 2003 US Midwest blackout [2].

Power grid infrastructure is experiencing a significant shift from the traditional electricity grid to the smart grid. The electricity demand of consumers has sharply increased in recent years. There is increasing interest in integrating renewable resources into the power grid, in order to decrease greenhouse gas emissions. Demand-side management (DSM), such as dynamic pricing, and demand response programs are used to improve the reliability of the grid. These new requirements and the aging of the existing grid make the modernization of the grid infrastructure a necessity. The smart grid incorporates new technologies such as advanced metering, automation, communication, distributed generation, and distributed storage [3]. The smart grid can optimize electricity generation, transmission, and distribution, reduce peaks in power usage, and sense and prevent power blackouts [4]. Therefore, the smart grid has the potential to significantly improve the efficiency and reliability of the power grid.

The smart grid is composed of a pair of infrastructures: a physical infrastructure and a cyber infrastructure [1], [5]. The electrical energy flows over the physical infrastructure. The cyber infrastructure is a large number of communication and computing networks, including wide-area monitoring, two way communications and enhanced control functions, which allows the interaction and feedback of socio-economic networks through the energy market [6]. The physical infrastructure is tightly coupled with the cyber infrastructure. Due to the employment of information and communication technology, the smart grid is becoming one of the fundamental cyber-physical systems [2].

In the smart grid, demand-side management (DSM) is an important mechanism for improving the reliability of the grid by dynamically changing or shifting the electricity consumption [7]. DSM can help utilities operate more efficiently, reduce emission of greenhouse gases, and also decrease the cost for electricity consumers. DSM strategies include load shifting and control [8]–[10], dynamic pricing (e.g., real-time pricing, time-of-use pricing) [11]–[14], and incentive-based demand response (DR) [15]–[17]. Real-time pricing is one of the most important DSM strategies, where the prices offered by retailers change frequently to reflect variations in the cost of the energy supply [14], [18] and the electricity demand of the customers over time.

In an electricity market, retailers procure electricity from various electricity sources (e.g., the pool, electricity derivatives, and self-production units), and then sell it to customers [19]. These electricity sources have different characteristics, and these characteristics might change over time. For example, the pool price is uncertain and volatile, and the costs of the other electricity source options are generally higher than the expected pool price [19], [20]. In the smart grid, renewable energy sources are also integrated into the power grid. These renewable energy sources are highly intermittent in nature and often uncontrollable. Therefore, there is a tradeoff between different electricity sources. On the other hand, the electricity demand of the customers might vary with time. Therefore, retailers need to make effective decisions about electricity sources, the electricity amount they procure and the price to offer to the customers.

There is some work in the literature related to retail electric power operations. Triki *et al.* discussed the real-time pricing with an adjustable customer base line [21]. Carrion *et al.* presented a stochastic programming methodology to determine the optimal retail price based on fixed pricing and the amounts of power procured from the pool and forward contracts [22]. Karandikar *et al.* used a capital asset pricing model to determine the electricity prices for retailers [23]. Celebi *et al.* developed a computable equilibrium model to estimate the time-of-use (TOU) rates based on the costs of different power generation [24]. Yusta *et al.* discussed how different price strategies affect the retailers' profit [25]. Gabriel *et al.* analyzed a set of strategies available to the retailers to determine the forward loads [26]. Gabriel *et al.* proposed a stochastic optimization model to determine the optimal forward loads and retail price [27].

Most of the existing work mainly focuses on one or two decisions, price decision, electricity source decisions or the electricity amount they procure decisions, which need to be made by retailers. These strategies are mainly for the retailers in the traditional power grid. To the best of our knowledge, no much work has been done for making optimal decisions about electricity sources and the amount that retailers should procure and the price to offer to the customers in the smart grid, especially when real-time pricing DSM is used. It is also very important to analyze how the retailer interacts with its customers and how its decisions affect the customers' satisfaction level, taking the impact of supply uncertainty into consideration.

In this paper, we propose a novel game-theoretical decision-making scheme for electricity retailers in the smart grid, where real-time pricing DSM is used. We assume that retailers are price-taking retailers, who do not affect the prices offered by the supply sources. We use various utility functions to model the electricity customers' preferences and electricity consumption patterns. A real-time demand response scheme is used by the customers to adjust their electricity demand to maximize their individual utility. We model and analyze the interactions between the retailer and electricity customers as a four-stage Stackelberg game [28]. The first three stages of the game analyze how the retailers should make decisions on which electricity sources to procure electricity from, how much electricity to procure, and what would be the optimal retail price to offer to the customers, in order to maximize profit. The fourth stage of the game shows how customers dynamically adjust their electricity demand with the offered retail price to maximize individual utility. Simulation results show the retailer and customers can achieve a higher profit and higher utility using our proposed decision-making scheme and how the system parameters affect the procurement and price decisions.

The rest of the paper is organized as follows. We model the interactions between the retailer and the customers as a four-stage Stackelberg game in Section II. The Stackelberg game is analyzed through backward induction in Section III. Simulation results are presented and discussed in Section IV. Finally, we conclude this study in Section V.

II. SYSTEM MODEL

In the smart grid, an advanced metering infrastructure (AMI) and smart meters are needed to provide two-way real-time communications between retailers and customers. There are two major types of information flows in the network: control data is exchanged between the retailers and the customers, and monitoring and metering data is transmitted from the customers to the retailers.

In order to make efficient decisions, each retailer needs to learn customers' preferences and electricity consumption patterns. Therefore, each retailer can be equipped with several software tools: a database, a data-mining engine and a decision-making tool. A database stores the historical electricity consumption value of each customer. The data-mining engine is used to forecast the future consumption of each customer through his/her historical consumption data. The decision-making tool helps retailers to make market decisions. Various incentive programs can also be used by the retailers to encourage customers to provide their accurate electricity demand values and their electricity preferences in advance.

A. REAL-TIME ELECTRICITY DEMAND MODEL FOR CUSTOMERS

In an electricity market, different electricity consumers require different levels of electricity, and might feel different level of satisfaction with the same price and amount of consumed electricity. In addition, a customer's satisfaction with the same level of electricity consumption can vary with time. The dynamic behaviors of customers can be accurately modeled by utility functions [29]. The utility of a customer can be modeled by a quadratic function with the following two requirements [13]: First, it is a concave function of the electricity consumption. Second, the corresponding electricity demand function of each customer needs to be linear, in order to simplify the analysis of pricing. Therefore, the utility function of an arbitrary user i can be defined as follows:

$$\mathcal{U}_i(p, d_i) = X_i d_i - \frac{\alpha_i}{2} d_i^2 - p d_i, \tag{1}$$

where X_i is a parameter that may vary among customers and at different times of the day, d_i denotes the electricity consumption level of customer i, α_i is a pre-determined parameter, and p is the price provided by the retailer.

Real-time pricing DSM is used by retailers, since it is an effective tool to guide and influence the electricity consumption behavior of customers [7]. Each customer adjusts his/her electricity consumption level in response to real-time electricity prices offered by the retailers to maximize its utility. The electricity consumption level of each customer can be calculated based on his/her utility function. We differentiate $\mathcal{U}_i(p, d_i)$ with respect to d_i to attain his/her consumption function. Therefore, The electricity consumption function $\mathcal{D}_i(p)$ of customer i can be expressed as follows:

$$\mathcal{D}_i(p) = \frac{X_i - p}{\alpha_i}. \tag{2}$$

If there are $|\mathcal{I}|$ users served by a retailer, where $|\mathcal{I}|$ is the cardinality of customer set $\mathcal{I}$, the total electricity demand is as follows:

$$\begin{aligned}\sum_{i\in\mathcal{I}} \mathcal{D}_i(p) &= \sum_{i\in\mathcal{I}} \left(\frac{X_i - p}{\alpha_i}\right) \\ &= \sum_{i\in\mathcal{I}} \frac{X_i}{\alpha_i} - \left(\sum_{i\in\mathcal{I}} \frac{1}{\alpha_i}\right) p = F - Gp. \end{aligned}\tag{3}$$

In the rest of the paper, F stands for $\sum_{i\in\mathcal{I}} \frac{X_i}{\alpha_i}$ and G stands for $\sum_{i\in\mathcal{I}} \frac{1}{\alpha_i}$ for simple presentation. In the smart grid, bi-directional communications between a retailer and its customers make it possible to implement this real-time demand response.

B. ELECTRICITY SUPPLY SOURCES FOR RETAILERS

There are various electricity supply sources in an electricity market. Retailers need to make decisions about which kinds of electricity sources and how much electricity they procure. In this paper, electricity sources are divided into two types: Option I: cheaper but uncertain, and Option II: more expensive but certain. Without loss of generality, the cost of electricity from the energy sources is modeled by a linear function of the procured electricity. In Option I, the cost function can be defined as:

$$\mathcal{C}(x) = C_m x, \tag{4}$$

where x denotes the electricity procured by the retailer and C_m is the price for a unit of electricity. We assume that only $x\beta$ electricity received by the retailer, where β $(0 \le \beta \le 1)$ is realization factor. This cost function can be used for modeling various electricity sources, such as self-production micro-grids. In the smart grid, various methods (such as electricity storage) have been used in the renewable energy generation or wholesale sides to increase the value of realization factor β. In our analysis, we assume that the retailer knows the distribution of the realization factor β beforehand. When such information is not available, the retailer can learn the distribution over time through machine learning [30], where the retailer uses the realization factor of previous time slots to update the distribution of β. The cost function of Option II can be defined as:

$$\mathcal{C}(x) = C_g x, \tag{5}$$

where x denotes the electricity procured by the retailer, and C_g is the price for a unit of electricity. The above two cost functions are quite general and can be extended to the situations where the actual usage follows other empirical distribution functions.

C. A FOUR-STAGE STACKELBERG GAME MODEL

Each electricity retailer needs to make decisions about how much electricity to procure, from which sources, and what price to offer to customers in order to maximize its profit. The customers then adjust their electricity demands based on the price offered by the retailer. In this paper, we assume that electricity source Option I is cheaper than electricity source Option II. The proposed Stackelberg game model can be easily adjusted for different situations. The retailer will make sequential decisions illustrated in Fig. 1 to maximize its profit, for the following reasons: first, the retailer should procure electricity from electricity source Option I first, and then procure electricity from electricity source Option II only if Option I does not provide enough electricity. If the retailer makes all three decisions simultaneously, it is likely to over-procure expensive electricity to avoid having too little electricity when is small. Second, making price decisions at the same time as procurement decisions makes it harder to ensure that the electricity supply equals the electricity demand. In order to capture these characteristics, we model and analyze the interactions between a retailer and its customers as a four-stage Stackellberg game [31] illustrated in Fig. 1 as follows:

- Stage I: The electricity retailer, as the Stackelberg leader, first decides the amount of electricity E_m procured from electricity source Option I with realization factor β.
- Stage II: The retailer then decides the amount of electricity E_g procured from electricity source Option II, based on the received electricity level in stage I.
- Stage III: The retailer decides the real-time price p to offer to the customers based on the total electricity supply.
- Stage IV: The customers, who are the followers in the Stackelberg game, adjust their individual electricity demand to maximize their individual utility.

In our paper, we assume that the realization factor β follows a uniform distribution in [0, 1]. However, the main engineering insights are still held with arbitrary distributions of realization factor β. In the following, we will analyze this four-stage Stackelberg game, and show how various system parameters affect the decisions.

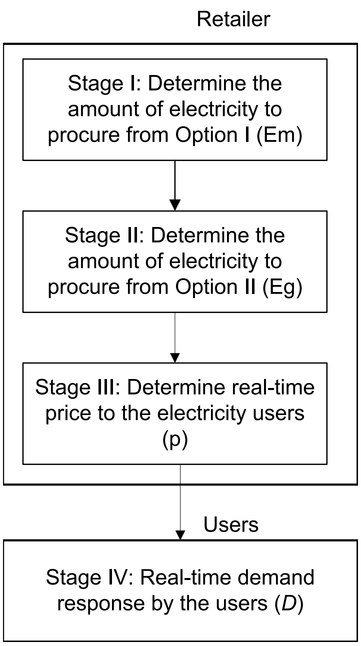

FIGURE 1. A four-stage Stackelberg game proposed for modeling the interactions between a retailer and its customers.

III. FOUR-STAGE STACKELBERG GAME ANALYSIS

A common solution concept for a multi-stage Stackelberg game is the subgame perfect equilibrium (SPE) [32]. Backward induction, which captures the sequential dependence of the decisions in the stages of the game, is a general method to determine the SPE [32], [33]. We first analyze how the customers adjust their individual electricity demand to maximize their utility based on the price offered by the retailer in stage IV. Then we analyze how the retailer makes real-time price decisions in stage III. We finally analyze the retailer's procurement decisions in stage II and in stage I.

A. REAL-TIME ELECTRICITY DEMAND IN STAGE IV

In this stage, customers determine their electricity demands given the unit price p announced by the retailer in stage III, which has been explained in Subsection II-A. We assume that the retailer knows individual customers' consumption patterns and preferences.

B. OPTIMAL REAL-TIME PRICING STRATEGY IN STAGE III

The retailer's profit, the difference between the revenue generated from selling the electricity and total cost of procuring the electricity, can be calculated as follows:

$$\mathcal{R}(E_m, \beta, E_g, p) = \min\left(p \sum_{i\in\mathcal{I}} \mathcal{D}_i(p), p(E_m\beta + E_g)\right) - (E_m C_m + E_g C_g), \quad (6)$$

since the retailer can only satisfy the electricity demand up to its supply. In this stage, the retailer needs to determine the optimal price to offer the customers, considering the total demand in (3) and the total electricity supply received in stages I and II, in order to maximize the profit. Therefore, the largest possible profit in stage III can be calculated as follows:

$$\mathcal{R}_{III}(E_m, \beta, E_g) = \max_{p\geq 0} \mathcal{R}(E_m, \beta, E_g, p). \quad (7)$$

Maximizing the retailer's profit is the same as maximizing its revenue, since the amounts of electricity E_m and E_g are given and therefore the total cost $C_mE_m + C_gE_g$ is already fixed in this stage. Therefore, the optimal price should meet the following requirement:

$$\max_{p\geq 0} \min\left(p \sum_{i\in\mathcal{I}} \mathcal{D}_i(p), p(E_m\beta + E_g)\right). \quad (8)$$

Let us define electricity demand $D(p) = p\sum_{i\in\mathcal{I}} \mathcal{D}_i(p)$ and electricity supply $S(p) = p(E_m\beta + E_g)$. Fig. 2 shows three possible relationships between $D(p)$ and $S(p)$, depending on the total electricity supply $E_m\beta + E_g$. Three possible choices of $S(p)$ are described as $S_j(p)(j = 1, 2, 3)$. The relationships are as follows:

1) $S_1(p)$ does not intesect $D(p)$, which is called an excessive supply regime.

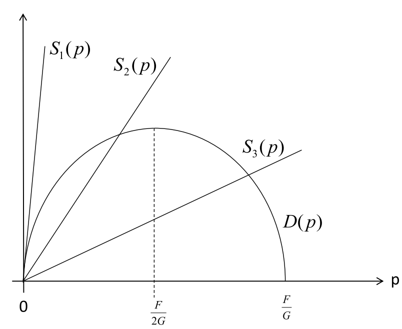

FIGURE 2. Different intersection cases of $D(p)$ and $S(p)$.

2) $S_2(p)$ has only one intersection with $D(p)$, where $D(p)$ has a non-negative slope. This is also called an excessive supply regime.
3) $S_3(p)$ has only one intersection with $D(p)$, where $D(p)$ has a negative slope. This is called a conservative supply regime.

In the excessive supply regime, $\max_{p\geq 0}\min(S(p), D(p)) = \max_{p\geq 0} D(p)$. In this regime, the total electricity supply is higher than the total electricity demand at the optimal price. Therefore, in the excessive supply regime, some electricity is left unsold. In the conservative supply regime, the revenue of the retailer is maximized at the unique intersection point of $D(p)$ and $S(p)$.

Theorem 1: The optimal electricity price and the corresponding maximum profit of the retailer in Stage III can be summarized in Table 1.

Proof: Taking the second derivative of $D(p)$, we get

$$\frac{\partial^2 D(p)}{\partial p^2} = -2p < 0. \tag{9}$$

Therefore, $D(p)$ is a concave function over p, and is maximized when $p = \frac{F}{2G}$. $S(p)$ is linearly increasing function over p.

When $E_m\beta + E_g < \frac{F}{2}$, $S(p)$ intersects with $D(p)$. $\min(D(p), S(p))$ is maximized at the intersection point, where price $p = \frac{F-E_m\beta-E_g}{G}$.

When $\frac{F}{2} \leq E_m\beta + E_g \leq F$, $S(p)$ intersects with $D(p)$. $\min(D(p), S(p))$ is maximized at the maximum value of $D(p)$, where price $p = \frac{F}{2G}$.

When $E_m\beta + E_g > F$, $S(p)$ does not intersect with $D(p)$. $\min(D(p), S(p))$ is maximized at the maximum value of $D(p)$, where price $p = \frac{F}{2G}$.

C. OPTIMAL ELECTRICITY PROCUREMENT STRATEGY IN STAGE II

In this stage, the retailer decides the amount of electricity E_g procured from Option II given the amount of electricity $E_m\beta$ obtained in stage I to maximize its profit, which can be described as follows:

$$R_{II}(E_m, \beta) = \max_{E_g\geq 0} R_{III}(E_m, \beta, E_g). \tag{10}$$

The above problem can be decomposed into two following subproblems based on the two supply regimes in Table 1. The first subproblem is to choose E_g such that the total electricity supply falls into the excessive supply regime in stage III, which can be described as follows:

$$R_{II}^{ES}(E_m, \beta) = \max_{E_g\geq \max\left\{\frac{F}{2}-E_m\beta,0\right\}} R_{III}^{ES}(E_m, \beta, E_g). \tag{11}$$

The second subproblem is to choose E_g such that the total electricity supply falls into the conservative supply regime in stage III, which can be described as follows:

$$R_{II}^{CS}(E_m, \beta) = \max_{0\leq E_g\leq \frac{F}{2}-E_m\beta} R_{III}^{CS}(E_m, \beta, E_g). \tag{12}$$

Theorem 2: The optimal amount of electricity to procure and the corresponding maximum profit of the retailer in stage II can be summarized in Table 2.

Proof: R_{III}^{ES} in (11) linearly decreases with E_g. Therefore, R_{III}^{ES} is maximized at the lower bound of the set (i.e., $E_g^* = \max\{\frac{F}{2} - E_m\beta, 0\}$).

If $E_m\beta > \frac{F}{2}$, the obtained electricity from Option I at the first stage is already in the excessive supply regime. Therefore, it is optimal to not procure any electricity at this stage.

If $0 \leq E_m\beta \leq \frac{F}{2}$, the optimal profit in (12) is always greater than or equal to that in (11), and it is enough to only consider the conservative supply regime. Since

$$\frac{\partial R_{III}^{CS}(E_m, \beta, E_g)}{\partial E_g} = \frac{F - 2E_m\beta - 2E_g}{G} - C_g, \tag{13}$$

$$\frac{\partial^2 R_{III}^{CS}(E_m, \beta, E_g)}{\partial {E_g}^2} = -\frac{2}{G} < 0. \tag{14}$$

Therefore, R_{III}^{CS} is a concave function over E_g. If $0 \leq E_m\beta \leq \frac{F-GC_g}{2}$, the optimal amount of electricity procured from Option II is $E_g^* = \frac{F-GC_g-2E_m\beta}{2}$. If $\frac{F-GC_g}{2} \leq E_m\beta \leq \frac{F}{2}$, $E_g^* = 0$.

Table 2 includes case CS1, case CS2, and case ES3 with different value sections of $E_m\beta$. The first two cases involve solving subproblem (12) in the conservative supply regime. The third case corresponds to the solution of subproblem (11) in the excessive supply regime. Although the procurement decisions of the retailer in cases CS2 and ES3 are the same, these two cases are listed separately since the retailer's profit in these two cases are different.

D. OPTIMAL PROCUREMENT STRATEGY IN STAGE I

In this stage, the retailer needs to decide optimal amount of electricity E_m to procure from Option I in order to maximize its expected profit by taking realization factor β into account, which can be described as follows:

$$R_I = \max_{E_m\geq 0} R_{II}(E_m), \tag{15}$$

where $R_{II}(E_m)$ is the expected profit of the retailer in stage II. This above problem can be decomposed into the following three cases, based on the value of E_m.

In the first case (corresponds to case CS1 in Table 2), E_m is less than or equal to $\frac{F-GC_g}{2}$, therefore $E_m\beta$ is always less than or equal to $\frac{F-GC_g}{2}$ for any value β. The expected profit of the retailer can be calculated as follows:

$$\begin{aligned} R_{II}^1(E_m) &= E_{\beta\in[0,1]}\Big[R_{II}^{CS1}(E_m, \beta)\Big] \\ &= \frac{F^2}{4G} + \frac{GC_g^2}{4} - \frac{FC_g}{2} + \left(\frac{C_g}{2} - C_m\right)E_m, \end{aligned}$$

which is a linear function of E_m. If $C_m > C_g/2$, the expected profit linearly decreases with E_m. If $C_m < C_g/2$, the expected profit linearly increases with E_m.

TABLE 1. Optimal price decision and maximum profit of the retailer in stage III.

Total Amount of Electricity Obtained in Stages I&II	Optimal Price $p*(E_m, \beta, E_g)$	Maximum Profit $R_{III}(E_m, \beta, E_g)$
Excessive Supply Regime: $E_m\beta + E_g \geq \frac{F}{2}$	$p^{ES} = \frac{F}{2G}$	$R_{III}^{ES}(E_m, \beta, E_g) = \frac{F^2}{4G} - E_gC_g - E_mC_m$
Conservative Supply Regime: $E_m\beta + E_g < \frac{F}{2}$	$p^{CS} = \frac{F-E_m\beta-E_g}{G}$	$R_{III}^{CS}(E_m, \beta, E_g) = \frac{(F-E_m\beta-E_g)(E_m\beta+E_g)}{G} - E_gC_g - E_mC_m$

TABLE 2. Optimal amount of electricity to procure and maximum profit in stage II.

Given $E_m\beta$ After Stage I	Optimal Amount of Electricity E_g^* Procured from Option II	Maximum Profit $R_{II}(E_m, \beta)$
(CS1) $E_m\beta \leq \frac{F-GC_g}{2}$	$E_g^{CS1} = \frac{F-GC_g-2E_m\beta}{2}$	$R_{II}^{CS1}(E_m, \beta) = \frac{F^2}{4G} + \frac{GC_g^2}{4} - \frac{FC_g}{2} + C_gE_m\beta - E_mC_m$
(CS2) $E_m\beta \in (\frac{F-GC_g}{2}, \frac{F}{2}]$	$E_g^{CS2} = 0$	$R_{II}^{CS2}(E_m, \beta) = \frac{(F-E_m\beta)E_m\beta}{G} - E_mC_m$
(ES3) $E_m\beta > \frac{F}{2}$	$E_g^{ES3} = 0$	$R_{II}^{ES3}(E_m, \beta) = \frac{F^2}{4G} - E_mC_m$

In the second case, E_m is within the set $(\frac{F-GC_g}{2}, \frac{F}{2}]$. Therefore, $E_m\beta$ can be in either case CS1 or CS2 in Table 2, depending on the value of β. The expected profit of the retailer can be calculated as follows:

$$\begin{aligned} R_{II}^2(E_m) &= E_{\beta\in\left[0, \frac{F-GC_g}{2E_m}\right]}\left[R_{II}^{CS1}(E_m, \beta)\right] \\ &\quad + E_{\beta\in\left[\frac{F-GC_g}{2E_m}, 1\right]}\left[R_{II}^{CS2}(E_m, \beta)\right] \\ &= \frac{(F-GC_g)^3}{24GE_m} + \left(\frac{F}{2G} - C_m\right)E_m - \frac{E_m^2}{3G}. \end{aligned}$$

The expected profit function in this case is a concave function, since its second-order derivative

$$\frac{\partial^2 R_{II}^2(E_m)}{\partial E_m^2} = \frac{(F-GC_g)^3}{12GE_m^3} - \frac{2}{3G} < 0, \tag{16}$$

as $E_m > \frac{F-GC_g}{2}$.

In the third case, E_m is greater than $\frac{F}{2}$. Therefore, $E_m\beta$ can be in any of the three cases in Table 2, depending on the value of β. The expected profit of the retailer can be calculated as follows:

$$\begin{aligned} R_{II}^3(E_m) &= E_{\beta\in\left[0, \frac{F-GC_g}{2E_m}\right]}\left[R_{II}^{CS1}(E_m, \beta)\right] \\ &\quad + E_{\beta\in\left[\frac{F-GC_g}{2E_m}, \frac{F}{2E_m}\right]}\left[R_{II}^{CS2}(E_m, \beta)\right] \\ &\quad + E_{\beta\in\left[\frac{F}{2E_m}, 1\right]}\left[R_{II}^{ES3}(E_m, \beta)\right] \\ &= \frac{-3F^2C_g + 3FGC_g^2 - G^2C_g^3}{24E_m} + \frac{F^2}{4G} - E_mC_m. \end{aligned}$$

The expected profit function in this case is a decreasing function, since the first-order derivative

$$\frac{\partial R_{II}^3(E_m)}{\partial E_m} = \frac{3F^2C_g - 3FGC_g^2 + G^2C_g^3}{24E_m^2} - C_m < 0, \tag{17}$$

as $E_m > \frac{F}{2}$. Therefore, the expected profit function achieves maximum value when $E_m = \frac{F}{2}$.

The expected profit of the retailer can be summarized as follows:

$$R_{II}(E_m) = \begin{cases} R_{II}^1(E_m), & 0 \leq E_m \leq \frac{F-GC_g}{2} \\ R_{II}^2(E_m), & \frac{F-GC_g}{2} < E_m \leq \frac{F}{2} \\ R_{II}^3(E_m), & E_m > \frac{F}{2}. \end{cases} \tag{18}$$

Since the maximum value of the expected profit in the second case is always greater than the maximum profit in the third case, there is no need to consider the third case. This means that the retailer is either in case CS1 or case CS2 in stage II, and in the conservative supply regime in Stage III.

Theorem 3: The optimal procurement strategy of the retailer and its corresponding maximum expected profit in stage I can be summarized in Table 3.

Proof: Table 3 includes two cases with different values of C_m and C_g.

When $C_m > \frac{C_g}{2}$, the expected profit $R_{II}(E_m)$ reaches its maximum when $E_m = 0$, which means that it is optimal for the retailer not to procure any electricity from Option I in this stage. In this situation, the retailer's maximal expected profit R_I^H only depends on the price of Option II.

When $C_m \leq \frac{C_g}{2}$, the highest expected profit R_I^L can be calculated as follows:

$$R_I = \max\left(\max\left(R_{II}^1(E_m)\right), \max\left(R_{II}^2(E_m)\right)\right). \tag{19}$$

TABLE 3. Optimal procurement strategy and maximum expected profit in Stage I.

	Optimal Amount of Electricity to Procure E_m^*	Maximum Expected Profit R_I
High Electricity Price of Option I: $C_m > \frac{C_g}{2}$	$E_m^* = 0$	$R_I^H = \frac{F^2}{4G} + \frac{GC_g^2}{4} - \frac{FC_g}{2}$
Low Electricity Price of Option I: $C_m \leq \frac{C_g}{2}$	$E_m^* = E_m^{L*}$	R_I^L in (21)

TABLE 4. The retailer's and electricity customers' equilibrium behaviors.

	High Price $C_m \geq \frac{C_g}{2}$	Low Price: $C_m \leq \frac{C_g}{2}$	
Optimal Amount to Procure from Option I E_m^*	0	E_m^{L*} solution to (20)	
Realization Factor β	$0 \leq \beta \leq 1$	$0 \leq \beta \leq \frac{F-GC_g}{2E_m^{L*}}$	$\beta > \frac{F-GC_g}{2E_m^{L*}}$
Optimal Amount to Procure from Option II E_g^*	$\frac{F-GC_g}{2}$	$\frac{F-GC_g}{2} - E_m^{L*}\beta$	0
Optimal Pricing $p*$	$\frac{F+GC_g}{2G}$	$\frac{F+GC_g}{2G}$	$\frac{F-\beta E_m^{L*}}{G}$
Highest Expected Profit R_I	$R_I^H = \frac{F^2}{4G} + \frac{GC_g^2}{4} - \frac{FC_g}{2}$	R_I^L in (21)	R_I^L in (21)
Customer i's Utility	$\frac{(2GX_i-F-GC_g)^2}{8G^2\alpha_i}$	$\frac{(2GX_i-F-GC_g)^2}{8G^2\alpha_i}$	$\frac{(GX_i-F+\beta E_m^{L*})^2}{2G^2\alpha_i}$

Since $R_{II}^1(E_m)$ is an increasing linear function over E_m, $\max(R_{II}^1(E_m))$ is achieved when E_m is equal to $\frac{F-GC_g}{2}$. For $R_{II}^2(E_m)$, the optimal amount E_m^{L*} is the solution to the following equation:

$$\frac{(GC_g - F)^3}{24GE_m^2} + \frac{F}{2G} - C_m - \frac{2E_m}{3G} = 0, \tag{20}$$

if E_m^{L*} lies in the interval of $[\frac{F-GC_g}{2}, \frac{F}{2}]$. Otherwise, E_m^{L*} equals $\frac{F-GC_g}{2}$ or $\frac{F}{2}$, depending on the value of the corresponding maximum expected profit. Therefore, the retailer's maximum expected profit R_I^L can be calculated as follows:

$$R_I^L = \frac{(F-GC_g)^3}{24GE_m^{L*}} + \left(\frac{F}{2G} - C_m\right)E_m^{L*} - \frac{E_m^{L*} \times E_m^{L*}}{3G}. \tag{21}$$

We summarize the retailer's equilibrium decisions from stage I to stage III and the equilibrium electricity demand of the customers in Table 4. Several interesting observations about Table 4 are described as follows.

Observation III.1. *The optimal pricing p^* is a non-increasing function in realization factor β.*

When price $C_m \geq \frac{C_g}{2}$, optimal price p^* is constant and independent of realization factor β. When $C_m \leq \frac{C_g}{2}$ and $\beta \leq \frac{F-GC_g}{2E_m^{L*}}$, optimal price p^* is also constant and independent of realization factor β. When $C_m \leq \frac{C_g}{2}$ and $\beta > \frac{F-GC_g}{2E_m^{L*}}$, optimal price decreases with the increase of realization factor β.

Observation III.2. *The retailer will procure electricity from Option I only if price C_m is lower than a threshold. Furthermore, the retailer will procure electricity from Option II only if the obtained electricity from Option I is below a threshold.*

Observation III.3. *The retailer's highest expected profit always benefits from the availability of Option I when its electricity price is low, i.e. $C_m \leq \frac{C_g}{2}$.*

E. THE RETAILER'S REALIZED PROFIT

The retailer's profit, for a given realization factor β, is defined as realized profit in this paper. When the price provided by Option I is low (i.e., $C_m \leq \frac{C_g}{2}$), the retailer's realized profit can be obtained base on the value of β. When the price of electricity Option I is high (i.e., $C_m > \frac{C_g}{2}$), the realized profit equals its expected profit R_I^H in Table 4, since no electricity will be procured from Option I.

Theorem 4: The retailer's realized profit is a strictly increasing function in realization factor β in the low cost regime.

Proof: When β is less than or equal to $\frac{F-GC_g}{2E_m^{L*}}$, the realized profit can be calculated as follows:

$$R_{II}^{CS1}(\beta) = \frac{F^2}{4G} + \frac{GC_g^2}{4} - \frac{FC_g}{2} - E_m^{L*}C_m + C_g\beta E_m^{L*}, \tag{22}$$

which is linearly increasing with β. When β is greater than $\frac{F-GC_g}{2E_m^{L*}}$, the realized profit can be calculated as follows:

$$R_{II}^{CS2}(\beta) = \frac{FE_m^{L*}\beta}{G} - \frac{(E_m^{L*})^2\beta^2}{G} - E_m^{L*}C_m, \tag{23}$$

which is increasing with β, since the first-order derivative of the profit function is:

$$\frac{\partial R_{II}^{CS2}(\beta)}{\partial\beta} = \frac{FE_m^{L*}}{G} - \frac{2(E_m^{L*})^2\beta}{G} > 0, \tag{24}$$

as $E_m^{L*} < \frac{F}{2}$.

IV. SIMULATION RESULTS AND DISCUSSIONS

In this section, we present simulation results to show the effectiveness of the proposed game-theoretical decision-making scheme and how the system parameters affect the decisions. In the simulations, there is one retailer serving electricity to ten customers. The parameters of the utility functions for these customers are set as follows: $X_i = 1$ ($i \in \{1, 2\}$), $X_i = 2$ ($i \in \{3, 4, 5\}$), $X_i = 3$ ($i \in \{6, 7, 8\}$), $X_i = 4$ ($i \in \{9, 10\}$), and α_i ($i \in [1, 10]$) = 2.5.

We first vary the price of electricity in Option I and Option II, and study how this affects the decisions of the retailer in stage I. Fig. 3 shows that for a given price C_g in Option II, the optimal amount E_m^* is constant at the beginning and then decreases as price C_m in Option I becomes higher, and drops to zero when $C_m \geq \frac{C_g}{2}$. Fig. 3 also shows that for a given price C_m, the optimal amount E_m^* is non-decreasing with the increase of price C_g, in which case procuring electricity from Option I becomes more attractive.

Next, we study how the decisions of the retailer in stage II are affected by price C_g in Option II, and price C_m and realization factor β in Option I. When price C_m is greater than or equal to half of price C_g, the optimal amount to procure from Option II only depends on price C_g. Therefore,

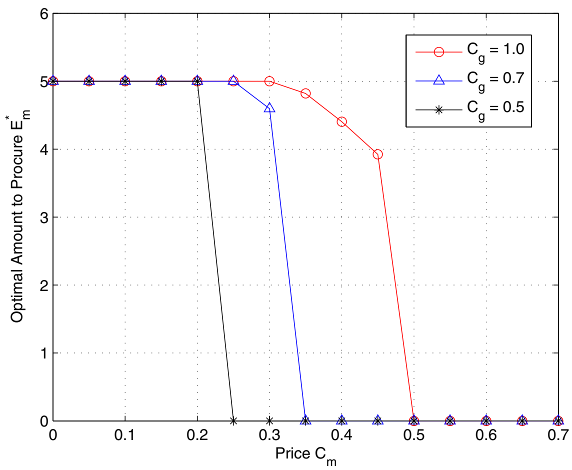

FIGURE 3. The optimal amount of electricity procured from electricity source Option I (E_m^*) with the changes of prices C_m in Option I and C_g in Option II.

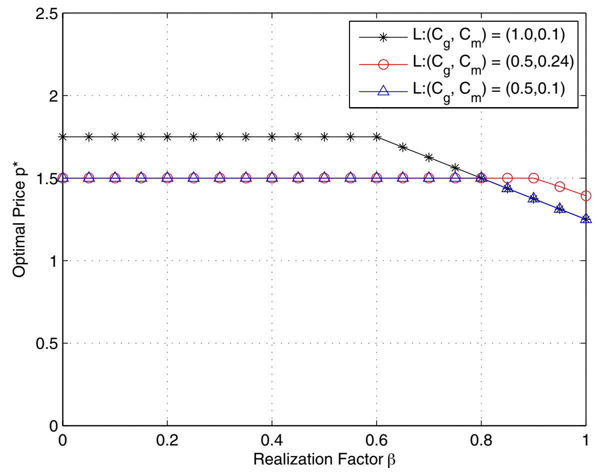

FIGURE 5. The optimal price offered to customers (p^*) with the changes of price C_g in Option II, price C_m in Option I, and realization factor β when $C_m < C_g/2$.

we only simulate the situation when price C_m is less than half of price C_g, corresponding to the low electricity price of Option I in Table 3 (denoted by "L"). Fig. 4 shows that the optimal amount E_g^* procured from Option II decreases with the increase of realization factor β. The reason for this is that a higher value β means more electricity is obtained from Option I, therefore there is a less need to procure electricity from Option II. The figure also shows that the optimal amount E_g^* increases with the increase of price C_m or the decrease of price C_g, in which case procuring electricity from Option II becomes more attractive.

We also investigate how the retailer's decisions in stage III change with price C_g, price C_m, and realization factor β. When price C_m is greater than or equal to half of the price C_g, optimal price only depends on price C_g. Fig. 5 shows the simulation results when price C_m is less than half of the price C_g. The figure shows that optimal price p^* is a constant (i.e., $\frac{F+GC_g}{2G}$) at the beginning, since the total amount of electricity obtained is $\frac{F-GC_g}{2}$. This constant increases with price C_g. When β is larger than a threshold $\frac{F-GC_g}{2E_m^{L*}}$, optimal price p^* decreases with the increase of the realization factor β. The threshold decreases with the increase of price C_g or the decrease of price C_m.

We then study how the retailer's procurement decisions with/without considering Option I affect its highest expected profit R_I with the change of price C_m. When $C_m \geq \frac{C_g}{2}$, expected profit does not depend on price C_m. Fig. 6 shows that when $C_m < \frac{C_g}{2}$, using our proposed decision-making scheme, the retailer achieves a higher expected profit than when only considering Option II. Fig. 6 shows the proposed decision-making scheme leads to a 1200% increase in

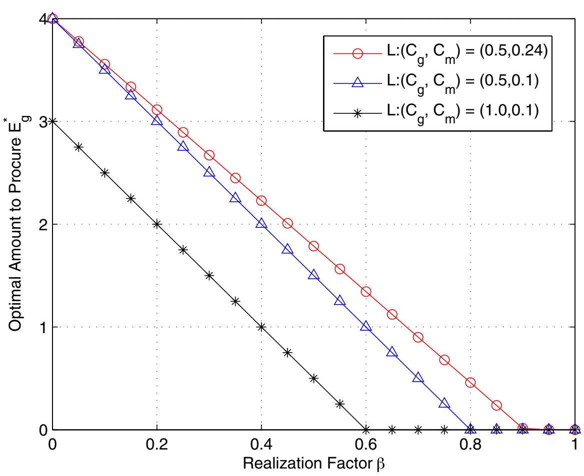

FIGURE 4. The optimal amount of electricity procured from Option II (E_g^*) with the changes of price C_g in Option II, price C_m in Option I, and realization factor β when $C_m < C_g/2$.

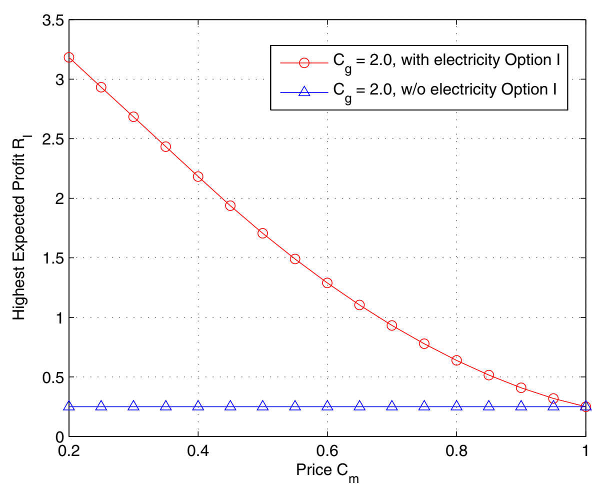

FIGURE 6. The highest expected profit (R_I) with/without considering Option I with the change of price C_m in Option I when $C_m < C_g/2$ (price C_g in Option II).

profit when $C_m = 0.2$. The figure shows that the highest expected profit decreases with the increase of price C_m. When price C_m equals half of price C_g, the retailer decides not to procure electricity from this option, and then the expected profit becomes the same as the profit without considering Option I.

We study how each user's utility is affected by price C_g, price C_m, realization factor β and its characteristic parameters. When price $C_m \geq \frac{C_g}{2}$, each user's utility is constant with the increase of realization factor. Fig. 7 shows that for a user, the utility is constant at the beginning with the increase of realization factor β when price $C_m < \frac{C_g}{2}$. The constant value decreases with price C_g (i.e., the increase of optimal price $p*$ offered to the user). When β is larger than $\frac{F-GC_g}{2E_m^{L*}}$ (decreasing with the value of price C_g), the user's utility increases, since optimal price p^* offered by the retailer decreases with the increase of the realization factor β. The crossing situation shows that realization factor has more influence on users' utility when price C_m is lower, and therefore a greater amount of electricity is procured from Option I. The figure also shows that a user's utility also increases with the characteristic parameter X_i in its utility function.

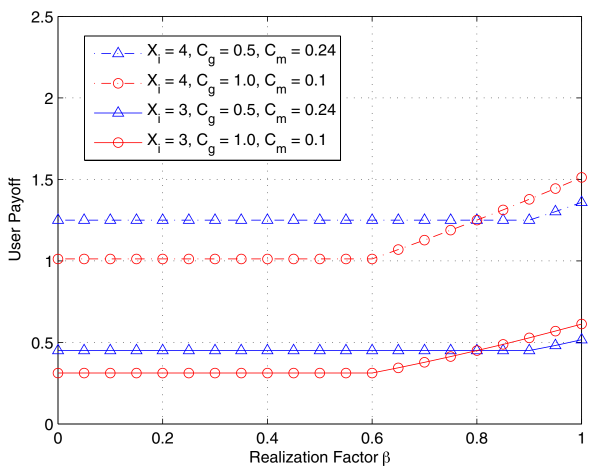

FIGURE 7. The utility of customer *i* with the change of realization factor β when $C_m < C_g/2$. X_i denotes the characteristic parameter in the utility function of an arbitrary user *i*. C_m and C_g denote the price in Option I and the price in Option II, respectively.

We also investigate how the variation of realization factor β with time affects the optimal price p^* offered by the retailer when price C_m is less than half of price C_g. Fig. 8 and Fig. 9 show that even though the realization factor changes frequently over time, the corresponding optimal price is not necessarily changing. This result shows that the retailer does not need to change the price offered to the users at every moment, which makes it possible for the proposed decision-making scheme to be implemented in the real-world applications. Fig. 8 shows that the optimal price only changes in 12 out 50 time slots, with cost $C_m = 0.98$, and cost $C_g = 2.0$. The reason is that since cost C_m is higher, the retailer does not procure large amount of electricity from Option I. As a result, the variability of β has very small impact on the optimal price. Fig. 9 corresponds to the case where $C_m = 0.70$, and $C_g = 2.0$. As price C_m is lower in Fig. 9, the retailer procures more electricity from Option I, and the impact of β on price is higher. Fig. 9 shows that the price changes in 28 out of 50 time slots.

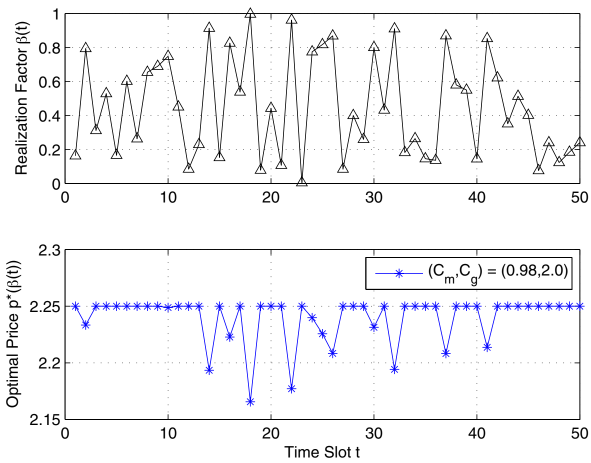

FIGURE 8. Optimal price p^* with the variation of realization factor β, price in Option I $C_m = 0.98$ and price in Option II $C_g = 2.0$.

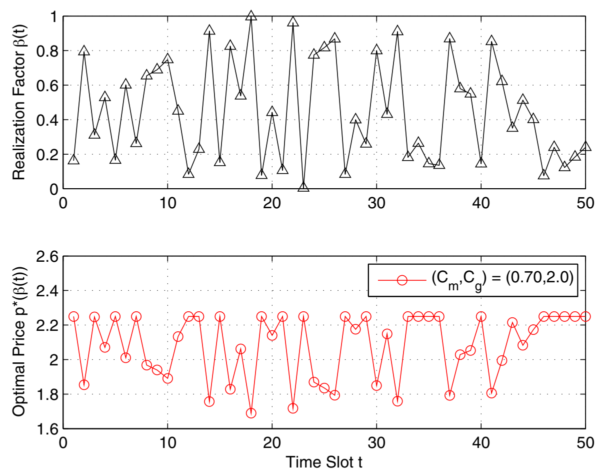

FIGURE 9. Optimal price p^* with the variation of realization factor β, price in Option I $C_m = 0.70$ and price in Option II $C_g = 2.0$.

We also check how optimal realized profit is affected by price C_g, price C_m and realization factor β. Fig. 10 shows that the realized profit increases with β, if price C_m is less than half of price C_g. The crossing feature of the two increasing curves shows the realization factor β has a larger impact on the realized profit when price C_m is low. When Option I is not considered in the procurement, the realized profit of the retailer is constant with the change of realization factor β.

The figure also shows that using our proposed decision-making scheme, the retailer can achieve a higher realized profit than when only considering Option II when β is higher than a certain level.

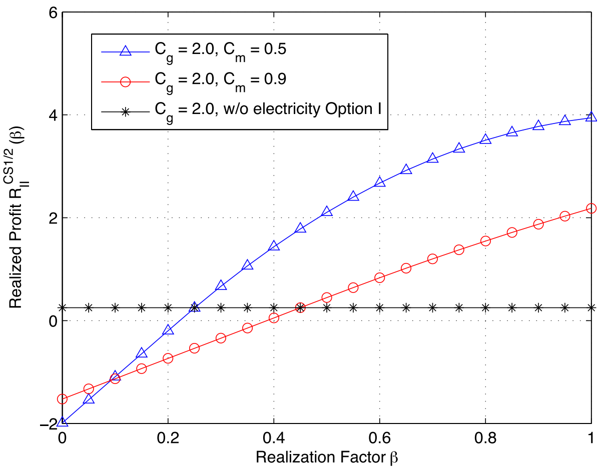

FIGURE 10. **Realized profit $R_{II}^{CS1/2}$ with the change of price in Option II C_g, price in Option I C_m and realization factor β with/without considering Option I.**

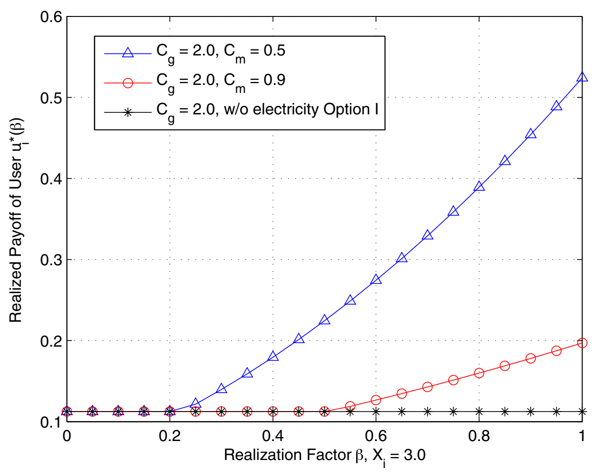

FIGURE 11. **Realized utility of user i with the change of realization factor β with/without considering Option I when $X_i = 3.0$. X_i denotes the characteristic parameter in the utility function of an arbitrary user i.**

We finally investigate how the realization factor β and prices C_g and C_m affect the realization utility of each user. Fig. 11 shows that the realization utility of a user is constant at the beginning, and then increases with β since the optimal price offered by the retailer starts to decrease. A lower C_m provides a higher realization utility when the realized factor is high. The figure also shows the proposed decision-making scheme leads to a 430% increase in the user's realization utility when $C_g = 2.0$ and $C_m = 0.5$, compared to the scheme that does not consider Option I.

V. CONCLUSION

In a retail electricity market, retailers need to procure electricity from various electricity sources with different characteristics and then sell it to customers. Therefore, retailers need to make effective decisions about electricity sources, the electricity amount they procure and the price to offer to the customers. In the smart grid, real-time pricing DSM will be widely used to dynamically changing or shifting the electricity consumption, and new electricity supply resources might advert. Retailers need to consider the new characteristics of the smart grid when they make market decisions.

In this paper, we have proposed a novel game-theoretical decision-making scheme for electricity retailers in the smart grid with DSM. We used various utility functions to model electricity customers' preferences and consumption patterns. The interaction between a retailer and its customers has been modeled as a four-stage Stackelberg game. The first three stages of the game analyze how the retailer should make optimal procurement and price decisions in order to maximize its profit. The fourth stage of the game shows that how customers dynamically adjust their electricity demands with the price offered by the retailer to maximize their individual utility. Backward induction is used to determine the SPE of the four-stage Stackelberg game, since it captures the sequential dependence of the decisions in the stages of the game. Simulation results have been presented to show the effectiveness of the proposed scheme and how the system parameters affect the decisions.

In our future work, competition among the retailers will be added to the proposed scheme, and the scheme will be extended to situations where complete information about customers' utility and preferences cannot be obtained. In this situation, the system needs to be modeled as a dynamic game with incomplete information. More elaborate economic models such as screening and signalling [34] become relevant.

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