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Real-Time Pricing Decision Based on Leader-Follower Game in Smart Grid

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Abstract The real-time pricing plays an important role in demand-side management for smart grid. In this paper, we study real-time pricing strategy of electricity retailers by means of game theory in smart grid. The retailers are in the game situation where there is one leader with multi-followers. We propose a real-time electricity demand function and analyze the interactions between the retailers, then obtain its equilibrium solution. The analysis and simulation results of the equilibrium solution show the effectiveness of the proposed method.

Keywords smart grid; demand-side management; real-time pricing; game theory

1 Introduction

The development of the contemporary economy and industry leads to the rapid growth in energy demand, therefore how to solve the energy shortage is an urgent issue to be solved. Smart grid, as the future area of the development of electric grid^[1,2] and a positive means to solve the shortage of energy, is expected to play a vital role. Demand-side management (for short DSM) has been one of the important topics which aim to solve the matching problem between enhanced demand for electricity and efficiency of supply, taking the user effectiveness, cost and price into account because it can be used to change the behavior of energy consumption.

The research based on the demand-side management has drawn a lot of attention. Various DSM solutions have been designed or investigated in a number of publications with a strong focus on the needs of supply adjustment, user utility maximization and cost reduction. These researches are based on convex programming, machine learning and game theory, see for instance, [3–8], but fail to reflect the value and cost of electricity at different periods in time by giving users varying electricity price.

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As the core content and the economic lever in the electricity market, the price plays a decisive role in electricity trading by regulating. The factors affecting the price are diverse. The traditional electricity pricing theory is not effective to reflect the security status of the power system properly. Deriving from short-run marginal cost theory, the real-time pricing (for short RTP) is based on the instantaneous supply-demand balance of the power system, and take into account the safe operation of the power system. Therefore, the RTP is not only an effective regulation means of the electricity market, but also an essential DSM strategy which achieves truly effective demand response and in which users actively adjust the load, shift the load, and optimize the allocation of resources.

RTP is a new approach to DSM, which has been dealt with in many publications. Mohsenian-Rad and Leon-Garcia^[6] developed a local residential load control method in the RTP environment, where each device runs along with the minimization of electricity payment and the waiting time as a response to the changes in the real time electricity tariffs. Asadi et al.^[9] set up an optimization model to maximize the benefit of users, in which users adjust their hourly energy consumption according to the real-time hourly price information. Asadi and Xu^[9,10] proposed a RTP algorithm so as to maximize the benefit of all users in the system and minimize the cost of electricity suppliers on the condition that the total power consumption is kept lower than the generation capacity. Mohsenian-Rad et al.^[6] proposed a residential load control scheme based on the feasibility of real-time pricing calculation and automatic optimization in the retail electricity market. However, these researches have not considered the effect of the interaction between different retailers on RTP.

The focus of this paper goes as follows.

- 1) We propose a one leader with multi-followers game decision for multiple retailers in the electricity market in order to maximize the profits of all retailers while considering the user demand response through the use of real-time pricing DSM.
- 2) We use a new utility function to simulate the power users' preferences and electricity consumption patterns. Retailers plan how much power to buy and at what price to sell to the users to maximize their revenues. The electricity demand function is re-constructed to describe how the different price of retailers affects real-time pricing decision.
- 3) We conduct an example using a collection of data to obtain the equilibrium solution by deducing. With an appropriate parameter, the simulation results demonstrate the effectiveness of the proposed model.

Our work differs from some related literatures in the following aspects: [6] and [8] only consider how the competition between retailer and users affects real-time pricing, while we study the optimization problem taking into account the impact of the competition between multiple retailers on the real-time pricing; compared with [14], we use a new demand function of electricity retailers and a different game model to characterize how the competition between different electricity retailers affect the real-time pricing. To our best knowledge, no research uses the bi-level game model to study the real-time pricing from the perspective of the electricity fellow retailers in the electricity supply market.

The remainder of this paper is organized as follows: Section 2 describes the system model and its symbol; Section 3 proposes a one leader with multi-followers game model to describe

the competition between different retailers in the electricity market; Section 4 solves the game model; Section 5 focuses on the model simulation and numerical analysis, and the final conclusions of this paper are given in Section 6.

2 System Model

Generally speaking, in the deregulated electricity market, sometimes there exist multiple electricity retailers. Retailers maximize their income through adjusting real-time price, based on user demand response according to the user's consumption patterns and preferences.

2.1 Real-Time Electricity Demand Model

1) Utility function of risk users

Different types of users have different power consumption demands in the electricity market. The price provided to the traditional electricity users is stable, while the short-term risk users always consume more electricity at lower price, which can be described using utility function^[12,13]. The utility function of risk users is same with the function used in most cases (see [14]) as follows

$$U(p,d) = Xd - \frac{\alpha}{2}d^2 - \xi pd \tag{1}$$

where X is a parameter which varies with different users and time, d denotes electricity demand of the risk users, ξ is the price elasticity of electricity demand, p denotes the price electricity retailer offers and α is a given parameter in advance. Real-time pricing DSM is used as an effective tool to affect electricity demand of users. The electricity demand function D(p) of each risk user can be obtained by maximizing the utility function

$$D(p) = \frac{X - \xi p}{\alpha} \tag{2}$$

2) Electricity demand function of retailers

Let N denote electricity retailers coexisting in the deregulated electricity market. Different retailers offer different prices for different risk power users, and power users can shift to purchase electricity from other electricity retailers who offer lower price. [11–14] described the electricity demand function of electricity retailer i as

$$D_i(p) = D_i - \xi_i p_i + \sum_{n=1, n \neq i}^{N} v_{i,n} p_n$$
(3)

where $p = (p_1, p_2, \dots, p_N)$ is the price vector of all electricity retailers, D_i is a parameter which varies with different users and time, reflecting the market size, scale and investment services. $\xi_i(0 < \xi_i < 1)$ is the price elasticity of electricity demand of retailer, and p_i denotes the price retailer i offers. $v_{i,n}(0 \le v_{i,n} \le 1)$ means the proportion of electricity demand flows from retailer i once the price offered by retailer i is given. The demand function mainly reflects the electricity price's influence on electricity demand through $v_{i,n}$, but this approach fails to reflect the retailers' price competition. Inspired by [15, 16], we adjust the electricity demand function as follows

$$D_i(p) = D_i - \xi_i p_i + \theta \sum_{j=1, j \neq i}^{N} (p_j - p_i) = D_i - \xi_i p_i + (N-1)\theta \left(\frac{\sum_{j=1, j \neq i}^{N} p_j}{N-1} - p_i\right)$$
(4)

where the mean of D_i , ξ_i same to those in (3), parameter $\theta \geq 0$ represents the sensitivity of price competition among electricity retailers, in other words, the market size one retailer obtains by offering a unit price lower than other retailers.

2.2 Revenue of Electricity Retailers

Each power retailer in the electricity market has two different types of income. Let the price offered to traditional users and the number of traditional users served by retailer i be constant P_i and M_i respectively. Retailer i can offer optimal response price to risk users based on user's demand response and other retailers' price, C_i denotes the procurement unit electricity cost. The profit function of retailer is denoted as follows:

$$R_{i}(p) = D_{i}(p)p_{i} + M_{i}P_{i} - [D_{i}(p) + M_{i}]C_{i}$$

$$= \left[D_{i} - \xi_{i}p_{i} + (N-1)\theta\left(\frac{\sum_{j=1, j\neq i}^{N} p_{j}}{N-1} - p_{i}\right)\right](p_{i} - C_{i}) + M_{i}(P_{i} - C_{i})$$
(5)

where $p_i \geq C_i, P_i \geq C_i$.

3 One Leader with Multi-Followers Real-Time Pricing Game

A plurality of electricity retailers coexist in a deregulated electricity market. All retailers hope to maximize their income by price adjustment as a response to user demand. When each retailer has the complete information of other retailers' price strategy, the optimal reaction function and equilibrium price can be used to describe the real-time pricing problem. The optimal reaction of each retailer is offering his optimal bidding to achieve maximum profit by referring to other retailers' bidding. Since positions and scale of retailers are different, their status decisions in the electricity market are not the same. The strong retailers are often in a leadership position, enjoying the priority to make price decisions, while the other small retailers follow the strong retailers to make price decision. Since all retailers affect each other, the analysis of real time pricing is just a game problem.

The leader-follower game, also called the Stackelberg game, is proposed by Stackelberg in [17]. From the earliest one leader with one follower game to one leader with multi-followers game, multi-leaders with multi-followers game, leader-follower differential game and nonsmooth leader-follower game^[18], the leader-follower game obtains considerable development. Various algorithms for the Stackelberg game models are well studied^[19], which are also widely used in the engineering and economy in the real world. We will propose a one leader with multi-followers game model for the coexisting retailers in electricity market. According to the game model, the first retailer is the leader, the others are followers interacting with each other, and retailers are perfectly rational. The classic one leader with multi-followers game model is as follows:

$$\min_{x} F(x, y_{1}, y_{2}, \dots, y_{n})$$
s.t. $G(x, y_{1}, y_{2}, \dots, y_{n}) \leq 0$

$$H(x, y_{1}, y_{2}, \dots, y_{n}) = 0$$
(6)

where y_i is the solution to the following optimization problem

$$\min_{y_i} \quad f_i(x, y_1, y_2, \dots, y_n)
\text{s.t.} \quad g_i(x, y_1, y_2, \dots, y_n) \le 0
\quad h_i(x, y_1, y_2, \dots, y_n) = 0$$
(7)

Definition 1 For every decision x in the upper level problem, $(y_1*, y_2*, \dots, y_n*)$ is called Nash equalization solution in lower level if there exists $(y_1*, y_2*, \dots, y_n*)$ satisfying

$$f_i(y_1*, y_2*, \cdots, y_{i-1}*, y_i*, y_{i+1}*, \cdots, y_n*) \le f_i(y_1*, y_2*, \cdots, y_{i-1}*, y_i, y_{i+1}*, \cdots, y_n*)$$
for $\forall (y_1*, y_2*, \cdots, y_{i-1}*, y_i, y_{i+1}*, \cdots, y_n*), i = 1, 2, \cdots, n.$

Definition 2 Let x* be a feasible decision vector in the upper level problem and let (y_1*, \dots, y_n*) be a corresponding Nash equilibrium solution for the vector. If the inequality

$$F(x*, y_1*, \cdots, y_n*) \le F(x, y_1*, \cdots, y_n*)$$

holds for any $x \in U_L$ and the corresponding Nash equilibrium solution, $(x*, y_1*, \dots, y_n*)$ is called the Stackelberg-Nash equilibrium solution to the one leader with multi-followers game.

Next, we model the strategic interaction between a big retailer and the other N-1 small retailers as a one leader-follower game model with one leader and N-1 followers. The $u_L(\text{price }p_L)$ denotes leader's strategy(electricity), U_L denotes the leader's strategy space, $u_{F_i}(i=1,2,\cdots,N-1)$ denotes strategy of the rest followers $F_i(i=1,2,\cdots,N-1)$ (price p_i), and U_{F_i} denotes the strategy space of follower $i(i=1,2,\cdots,N-1)$'s. Leader's payoff function is denoted by $J_L(u_L,u_{F_1},\cdots,u_{F_{N-1}})$, and the payoff function of follower F_i is denoted by $J_{F_i}(u_L,u_{F_1},\cdots,u_{F_{N-1}})$. By (5) the profit function of the leader in the market is

$$R_L(p) = \left[D_L - \xi_L p_L + (N-1)\theta \left(\frac{\sum_{j=1, j \neq i}^N p_j}{N-1} - p_L \right) \right] (p_L - C_L) + M_L(P_L - C_L)$$
 (8)

the profit function of each follower is

$$R_i(p) = \left[D_i - \xi_i p_i + (N-1)\theta \left(\frac{\sum_{j=1, j \neq i}^{N-1} p_j}{N-1} - p_i \right) \right] (p_i - C_i) + M_i (P_i - C_i)$$
 (9)

We thus have

$$J_L(u_L, u_{F_1}, \dots, u_{F_{N-1}}) = R_L(p)$$

$$J_{F_i}(u_L, u_{F_1}, \dots, u_{F_{N-1}}) = R_i(p)$$
(10)

The steps of solving the one Leader with multi-followers game are as follows:

Step 1 For each given strategy u_L of the leader, each follower tries to obtain the optimal reaction strategy $R_{F_i}(u_L, u_{F_1}, \dots, u_{F_{N-1}})$ based on maximizing his own objective function by considering the bidding strategies of other followers as $\max_{u_{F_i} \in U_{F_i}} J_{F_i}(u_L, u_{F_1}, \dots, u_{F_{N-1}})$.

Step 2 As for the leader, he tries to maximize his own objective function by taking into account all followers' bidding strategies as follows $\max_{u_L \in U_L} J_L(u_L, R_{F_1}, \dots, R_{F_{N-1}})$.

Step 3 Assuming u_L* is the optimal solution of leader, $u_{F_i}*=R_{F_i}(u_L*,u_{F_1}*,\cdots,u_{F_{i-1}}*,u_{F_{i+1}}*,\cdots,u_{F_{N-1}}*)$, then $(u_L*,u_{F_1}*,\cdots,u_{F_i}*,\cdots,u_{F_{N-1}}*)$ is the optimal Stackelberg strategy.

4 The Solution of Model

According to the method in the last section, we have to find the followers' optimal reaction functions given leader's strategy p_L , and also find the optimal strategy of the leader on the basis of the determined followers' reaction function. In fact, the optimal strategy of the game is available if solutions of the leader and the followers exist.

To decide effectively the above process amounts to solve the bilevel programming. The upper problem is

$$\max J_L(u_L, u_{F_1}, \dots, u_{F_{N-1}}) = \max J_L(p_L, p_1, \dots, p_{N-1})$$

$$= \left[D_L - \xi_L p_L + (N-1)\theta \left(\frac{\sum_{j=1, j \neq i}^{N-1} p_j}{N-1} - p_L \right) \right] (p_L - C_L)$$

$$+ M_L(P_L - C_L) \tag{11}$$

For each retailer $i(i = 1, 2, \dots, N - 1)$ in lower level programming, the solution p_i is the optimal solution to the following planning problem

$$\max J_{F_i}(u_L, u_{F_1}, \cdots, u_{F_{N-1}}) = \max R_i(p)$$

$$= \max \left[D_i - \xi_i p_i + (N-1)\theta \left(\frac{\sum_{j=1, j \neq i}^{N-1} p_j}{N-1} - p_i \right) \right] (p_i - C_i)$$

$$+ M_i(P_i - C_i)$$
(12)

For the *i*-th planning problem in lower level programming, the function $R_i(p)$ is concave with respect to p_i , then the maximum value of $R_i(p)$ can be achieved when $\frac{\partial R_i(p)}{\partial p_i} = 0$, in other words

$$\frac{\partial R_i(p)}{\partial p_i} = D_i - 2[\xi_i + (N-1)\theta]p_i + \theta \left(\sum_{i=1, i \neq i}^{N-1} p_j + p_L\right) + [\xi_i + (N-1)\theta]C_i = 0$$
 (13)

Similarly, for arbitrary $s \neq i (s = 1, 2, \dots, N - 1)$ in the lower level programming, we have

$$\frac{\partial R_s(p)}{\partial p_s} = D_s - 2[\xi_s + (N-1)\theta]p_s + \theta\left(\sum_{j=1, j \neq i}^{N-1} p_j + p_L\right) + [\xi_s + (N-1)\theta]C_s = 0$$
 (14)

To reduce the complexity of derivation, we set $\xi_i = \xi_s$, $C_i = C_s$. Then, (13) and (14) are equivalent to

$$\frac{\partial R_i(p)}{\partial p_i} = D_i - 2[\xi + (N-1)\theta]p_i + \theta \left(\sum_{j=1, j \neq i}^{N-1} p_j + p_L\right) + [\xi + (N-1)\theta]C = 0$$
 (15)

$$\frac{\partial R_s(p)}{\partial p_s} = D_s - 2[\xi + (N-1)\theta]p_s + \theta\left(\sum_{j=1, j \neq i}^{N-1} p_j + p_L\right) + [\xi + (N-1)\theta]C = 0$$
 (16)

Letting (15) subtract (16), we get equilibrium solution to the lower level programming which satisfies the following equation

$$p_i - p_s = \frac{D_i - D_s}{2\xi + (2N - 1)\theta} \tag{17}$$

Taking $s = 1, 2, \dots, i - 1, i + 1, \dots, N - 1$ in (17), we obtain

$$\sum_{j=1, j\neq i}^{N-1} p_j = (N-2)p_i - \frac{(N-2)D_i - \sum_{j=1, j\neq i}^{N-1} D_j}{2\xi + (2N-1)\theta}$$
(18)

Substituting Equation (18) to Equation (15), we have

$$p_{i}* = \frac{D_{i} + \theta p_{L} + [\xi + (N-1)\theta]C - \frac{\theta \sum_{j=1, j \neq i}^{N-1} (D_{i} - D_{j})}{2\xi + (2N-1)\theta}}{2\xi + N\theta}$$
(19)

Let $i = 1, 2, \dots, N-1$ in (19) and then the sum is available

$$\sum_{i=1}^{N-1} p_i * = \frac{\sum_{i=1}^{N-1} D_i + (N-1)\theta p_L}{2\xi + N\theta} + \frac{(N-1)[\xi + (N-1)\theta]C - \frac{\theta \sum_{i=1}^{N-1} \sum_{j=1, j \neq i}^{N-1} (D_i - D_j)}{2\xi + N\theta}}{2\xi + N\theta}$$
(20)

Substituting (20) into the upper programming leads to

$$R_{L}(p) = \left[D_{L} - \xi p_{L} + (N-1)\theta \left(\frac{\sum_{j=1, j \neq i}^{N} p_{j}}{N-1} - p_{L}\right)\right] (p_{L} - C) + M_{L}(P_{L} - C)$$

$$= (D_{L} - \xi p_{L})(p_{L} - C) + \theta \frac{\sum_{i=1}^{N-1} D_{i} + (N-1)\theta p_{L} + (N-1)[\xi + (N-1)\theta]C}{2\xi + N\theta} (p_{L} - C)$$

$$- \theta \frac{\frac{\theta \sum_{i=1}^{N-1} \sum_{j=1, j \neq i}^{N-1} (D_{i} - D_{j})}{2\xi + N\theta} (p_{L} - C) - (N-1)\theta p_{L}(p_{L} - C) + M_{L}(P_{L} - C)$$
(21)

Similarly, by $\frac{\partial R_L(p)}{\partial p_L} = 0$ we have

$$p_{L*} = \frac{(2\xi + N\theta)[D_{L} + M_{L} + \xi C + (N-1)\theta C] - \theta^{2}(N-1)C}{2\theta^{2}(N-1)^{2} + 2\xi(2\xi + 3N\theta - 2\theta)} + \frac{\theta[\sum_{i=1}^{N-1} D_{i} + (N-1)\xi C + (N-1)^{2}\theta C]}{2\theta^{2}(N-1)^{2} + 2\xi(2\xi + 3N\theta - 2\theta)} - \frac{\frac{\theta^{2}\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1}(D_{i}-D_{j})}{2\xi + (2N-1)\theta}}{2\theta^{2}(N-1)^{2} + 2\xi(2\xi + 3N\theta - 2\theta)}$$
(22)

The solution of model thus is properly obtained

$$p_{L}* = \frac{(2\xi + N\theta)[D_{L} + M_{L} + \xi C + (N-1)\theta C] - \theta^{2}(N-1)C}{2\theta^{2}(N-1)^{2} + 2\xi(2\xi + 3N\theta - 2\theta)} + \frac{\theta[\sum_{i=1}^{N-1} D_{i} + (N-1)\xi C + (N-1)^{2}\theta C]}{2\theta^{2}(N-1)^{2} + 2\xi(2\xi + 3N\theta - 2\theta)} - \frac{\frac{\theta^{2}\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1}(D_{i} - D_{j})}{2\xi + (2N-1)\theta}}{2\theta^{2}(N-1)^{2} + 2\xi(2\xi + 3N\theta - 2\theta)}$$

$$p_{i}* = \frac{D_{i} + \theta p_{L} + [\xi + (N-1)\theta]C - \frac{\theta\sum_{j=1,j\neq i}^{N-1}(D_{i} - D_{j})}{2\xi + (2N-1)\theta}}{2\xi + N\theta}$$
(23)

5 Analysis and Simulation of Model

In this section, we analyze equilibrium solution of the game model obtained in the last section. By (23), we know that

- 1) The real-time pricing of all electricity retailers is related to the purchasing power costs in market. The higher the purchase cost, the higher the equilibrium price.
- 2) The larger retailer market size, the higher the price, and the greater the profit. Especially the leader retailer living in a monopoly market is ensured to be affected less by the risk users because he serves more long-term customers. The price of the retailers increases in a timely manner when the number of long-term users increases and the other small electricity retailers also raise the price.
- 3) In what follows, we discuss the impact of sensitivity θ on the equilibrium price through numerical examples, and give the simulation results to verify the validity of the proposed dynamic real-time pricing decisions. Suppose the market consists of three electricity retailers, large retailer 1 and small retailer 2 and 3, let $\xi = 0.5$, $D_1 = D_2 = 1$, $D_L = 5$, C = 0.3, $M_L = 50$, considering the trend chart of the equilibrium price change when sensitivity θ varies between 0 and 1, as is shown below.

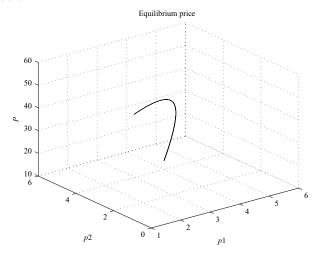


Figure 1 Equilibrium price change trend chart affected by θ

As can be seen from the chart the equilibrium prices of all retailers increase with the rise of sensitivity θ at the beginning time, and comparatively speaking, the equilibrium price of big retailer is lower, since the big retailer has his first-mover advantage with the increasing of electricity demand, and then reduces the price in order to win more risk users.

6 Conclusions

In this paper, we carry out some exploration in the marketization of electricity market and propose a one leader with multi-followers game decision for multiple electricity retailers competition in the market based on smart grid DSM's real-time pricing. This paves a way for making reasonable DSM rules under the near future smart grid platform. We also analyze the impact of strategic interactions between retailers of different status and types, and obtain

the equilibrium price solution. Compared with the previous works about real-time pricing for more retailers based on static or completely cooperative game theory, our model uses a different game model and also introduces sensitivity coefficient to examine its impact on the description of inter-retailer. Simulation results demonstrate the special impact of sensitivity coefficient on the equilibrium price. A more sophiticated model may be proposed to explore the effect of real-time pricing DSM strategy to bring more profit to the users and retailers in smart grid in the near future.

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