Strategy of Electricity Sales and Retail based on Double-layer Game

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Abstract. In this paper, a two-layer game model of users and retailers considering load management is constructed. The lower layer is the game between the users and the retailers. The analytic hierarchy process is used to establish the model of the users to select the retailer, and the market share of the retailer is updated by the evolutionary game. The upper layer is the game between the retailers. By using single-objective optimization and multi-company revenue-oriented algorithm, the electricity price strategy is adjusted. Through Matlab simulation, the model is valid, and the single-objective and multi-objective optimization strategies are compared to prove that the multi-objective optimization results are more in line with actual needs.

Keywords: two-layer game model; Matlab simulation; multi-objective optimization results; evolutionary game.

1. Introduction

With the recent years, the average electricity price of general industry and commerce has continued to decline, and the electricity price game space between electricity retailers has further narrowed. Therefore, the electricity retailer should take the service of user as the core and adjust the electricity price on the basis of providing high-quality services in order to obtain greater benefits.

There have been some studies on the application of game theory in electricity price strategies of electricity retailers. Reference [1] uses a dual-cycle Stackelberg game model to compensate the shortage of power resources of the system at a lower cost, and chooses to use a uniform price to compensate, which is not as intuitive for users as the time-sharing price. Literature [2] proposed a multi-sale e-commerce game model based on Bayesian theory, and established a user IRP decision model. E-sale providers would not change the current pricing strategy due to the maximization of their own immediate revenue. Literature [3] proposed a new algorithm for solving electronic bidding using multi-player matrix games for quickly and accurately finding the Nash equilibrium. Reference [4] constructed a market multi-agent game framework including generators, electricity retailers and users, and used reinforcement learning methods to find the optimal solution for electricity prices. The game analysis of the above literature does not consider value-added services.

Taking into account the deficiencies of the above studies, this paper builds a two-layer game model of users and electricity retailers considering load management.

2. Evolutionary Game

The evolutionary game is derived from biological evolution and genetic inheritance. Compared with traditional static games, it is based on the evolution of population rather than a single individual; it emphasizes bounded rationality; it emphasizes dynamic equilibrium, and the results will change with strategy changes, which is more in line with actual conditions.

2.1 The Users' Choices Model

Users mainly consider the following aspects to choose a retailer: power prices, market share, power supply reliability, and value-added services provided by power companies. This article adopts the Analytic Hierarchy Process (AHP) to build a model for users to choose an electricity supplier:

$$U_i^j = k_1 B_1 + k_2 B_2 + k_3 B_3 + k_4 B_4 \tag{1}$$

Where U_i^j is the benefit of the retailer j to users, B and k are the scores of the retailer and the weight of the indicator. In order to make the results converge faster and reduce the number gap caused by different units between indicators, the indicator scores are normalized uniformly.

The market share represents the degree of market acceptance of the electricity supplier, and users are often more confident about the electricity supplier with a high market share. Initially, the given occupancy rate is used, and then the selection situation updated by evolutionary games is selected.

Value-added services reflect the customer-oriented business philosophy of retailers. E-commerce vendors who are more attentive to users are more likely to be favored by users. Here, user satisfaction is used as the evaluation criterion:

$$EES = 1 - \frac{C_i^{'} - C_i}{C_i} \tag{2}$$

Where C_i and $C_i^{'}$ are the electricity sales payment before and after the launch of value-added services.

2.2 Evolutionary Dynamic Equation

The evolutionary game simulates the learning process in the population by duplicating dynamic equations, where the modified protocol indicates that each time after the evolutionary game, individuals are given the opportunity to re-select their own strategies and make changes to their strategy decisions:

$$\frac{\partial x_j}{\partial t} = \sum_{m=1}^{J} x_m \rho_{m \cdot j} \left[U(x) \right] - x_j \sum_{m=1}^{J} \rho_{j \cdot m} \left[U(x) \right] \tag{3}$$

Where x_j is the market share of the retailer j, and $\rho_{m \cdot j} \left[U(x) \right]$ is the proportion of users from the retailer m to the retailer j. In order to better show the changes in the market share of the two companies, the logit model was used to adjust:

$$\rho_{m \cdot j} \left[U(x) \right] = \frac{\exp \left[U_j(x) \right]}{\sum_{m=1}^{J} \exp \left[U_m(x) \right]} \tag{4}$$

Substituting equation (4) into equation (3), we can get:

$$\frac{\partial x_j}{\partial t} = \frac{\exp \left[U_j(x) \right]}{\sum_{j=1}^{J} \exp \left[U_j(x) \right]} - x_j = \rho_{m \cdot j} \left[U(x) \right] - x_j \tag{5}$$

When the operation reaches the evolution equilibrium, the market share of the two companies at this time is output, which is the user's choice under this strategy.

3. Electricity Price Strategy Formulation

3.1 Single Objective Optimization

The single-objective optimization aims to consider only the maximum revenue of its own company:

$$\max E_j = \sum_m \left\{ P(m) \left[\sum_{i \in I} \sum_{t \in T} p_{j \cdot i}(m \cdot t) q_{j \cdot i}(m \cdot t) \Delta t \right] \right\} - \sum_k P_{k \cdot j} Q_{k \cdot j} \tag{6}$$

The revenue of the electricity retailer is the difference between the sum of the electricity sales revenue to users in each period and the cost of purchasing electricity from the grid company.

In order to achieve this goal, the time-of-use electricity price for each period is adjusted and constrained by the peak-to-valley electricity price ratio:

$$p_{j,t} = \begin{cases} (1+\alpha_j)p_{0,j,t}, & t \in T_f \\ p_{0,j,t} & , t \in T_p \\ (1-\beta_j)p_{0,j,t}, & t \in T_g \end{cases} \tag{7}$$

Where α_j is the proportion of electricity price increase at peak time, β_j is the proportion of electricity price reduction at valley time, T_f, T_p and T_g are the peak, normal and valley time periods.

$$\mu_j = \frac{1+\alpha_j}{1-\beta_j} \tag{8}$$

The peak-to-valley electricity price ratio is generally between 1.96 and 5 [5].

3.2 Multi-objective Optimization

When researching power sales strategies, you can't just use yourself as the standard, you also need to consider the reaction of your opponents, so here we use the maximum revenue of the two power sales vendors as the goal and restrict it:

$$\begin{cases} \max E_m(x_1, u_1) \\ \max E_j(x_2, u_2) \\ s.t. \quad x_1 + x_2 = 1 \\ \quad 0 < x_1 < 1, 0 < x_2 < 1 \\ \quad 1.96 \le u_1 \le 5, 1.96 \le u_2 \le 5 \end{cases} \tag{9}$$

The market share of the two retailers is x_1 and x_2, the market share of each retailer is 1.

The two retailers will have the biggest revenue conflicts. Here we choose the NSGA-II algorithm that finds the fastest solution. The NSGA-II algorithm aims to find the Pareto solution set. In order to get the Pareto solution quickly, the NSGA-II algorithm performs fast non-dominated sorting and initial crowding degree calculation after initializing the population. Fast non-dominated sorting calculates the individual's dominated set and the individual's dominated set, traverses the population, obtains the Pareto level of each individual, and finally retains the highest Pareto level solution, which is the Pareto solution set.

In order to obtain the optimal compromise solution, the maximum satisfaction method is used to first calculate the fuzzy satisfaction of each individual:

$$\delta_{j,i} = \begin{cases} 1, & f_{j,i} \le f_j \min \\ \dfrac{f_j \max - f_{j,i}}{f_j \max - f_j \min}, & f_j \min < f_{j,i} < f_j \max \\ 0, & f_{j,i} \ge f_j \max \end{cases} \tag{10}$$

Where $\delta_{j,i}$ indicates satisfaction, $\delta_{j,i} = 1$ indicates full satisfaction, $\delta_{j,i} = 0$ and indicates total dissatisfaction.

4. Case Study

4.1 Single Objective Optimization

Select the characteristic daily load curve of commercial users in a certain area and manage the load. The curve is shown in Figure 1. Assume that there are two electricity sellers to choose from. One is an advantageous retailer, with power generation resources, which has a larger initial market share and a lower electricity price. The other is a disadvantaged retailer, who needs to purchase electricity from a power plant. The market share is relatively small and the electricity price is high. See Table 1 for time-sharing electricity prices of the two companies

Table 1. Time-of-use electricity price list of two retailers

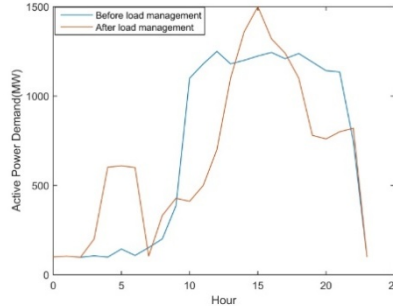| Electricity price(¥/kW·h) Period	Advantaged electricity retailer	Disadvantaged electricity retailer
0:00-6:00and22:00-0:00	0.4418	0.4700
6:00-8:00and12:00-18:00and21:00-22:00	0.7113	0.7820
8:00-12:00and18:00-21:00	1.1505	1.2520

Figure 1. Single-day load curve before and after commercial user load management in a certain area

Assume that the initial market share of the two retails is [0.7 0.3] and [0.5 0.5], respectively. Neither of the two retails performs load management, and only the inferior power retailer performs load management and the inferior retailer bases on load management. Three cases of adjusting electricity prices for evolutionary games and single-objective optimization analysis, The results of single objective optimization are shown in Table 2.

Table 2. Evolutionary game and single-objective optimization results under three scenarios

Scene	Advantaged electricity retailer		Disadvantaged electricity retailer	
	Market share (%)	Income (¥)	Market share (%)	Income (¥)
Neither advocate load management	62.18	8437.0	37.82	5601.2
Only disadvantaged retailer promotes load management	48.69	6606.9	51.31	6895.5
Disadvantaged retailer advocates load management +electricity price adjustment	26.90	3650.5	73.10	9002.6

Observing Table 2, comparing the three types of e-commerce sellers' revenues, it can be found that for inferior e-commerce vendors, after using load management, the revenue can catch up with the superior e-commerce vendors. After adjusting the time-of-use electricity price, the revenue increased by 30.56%. It can be seen that good value-added services can bring greater benefits to electricity retailers. By comparing the market share and the final revenue, it can be found that the final revenue of the electricity retailer is positively correlated with the market share, and the electricity retailer more favored by users will get greater revenue, which reflects the importance of serving users. However, the final strategy obtained by single-objective optimization has a large impact on the market, the market share changes too much, and the strategy change is easy to be perceived by opponents.

4.2 Multi-objective Optimization

The NSGA-II algorithm was selected to adjust the electricity price under the load management situation of the inferior power selling company only, and 200 populations were selected for 500 iterations for calculation and analysis. The result is shown in Figure 2.
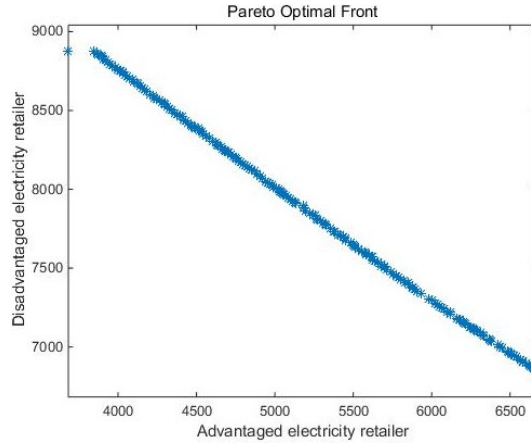
Figure 2. Pareto frontier under only disadvantage retailer adjust the price after promoting load management

In Figure 6, a series of point sets can be obtained through the NSGA-II algorithm, which is the Pareto front, and each point is a non-inferior strategy. Through dual-objective optimization, a strategy set can be selected for retailers. Compared with single-objective optimization, multi-objective optimization can obtain more strategies to choose according to their own needs.

The slope $|k|$ is the ratio of the incremental revenue of the two retailers under the price adjustment. When $0 < |k| < 1$, the adjustment of the electricity price strategy of the inferior retailer will yield more income than the other, and the smaller the slope is, the more advantageous the inferior retailer will be.

4.3 Comparison of Single-objective Optimization and Multi-objective Optimization

Table 3. Assume four scenarios

Scene 1	Neither retailer performs load management
Scene 2	Only inferior retailer performs load management
Scene 3	Only advantageous retailer performs load management
Scene 4	Both retailers perform load management

Assume that there are four scenarios in Table 4, which are analyzed by single-objective optimization and multi-objective optimization. Figure 3 is a comparison of the revenue of the two retailers. Figure 4 shows the market share and peak-to-valley price comparison of inferior retailer. The left side of the figure is the multi-objective optimization result, and the right side is the single-objective optimization result.
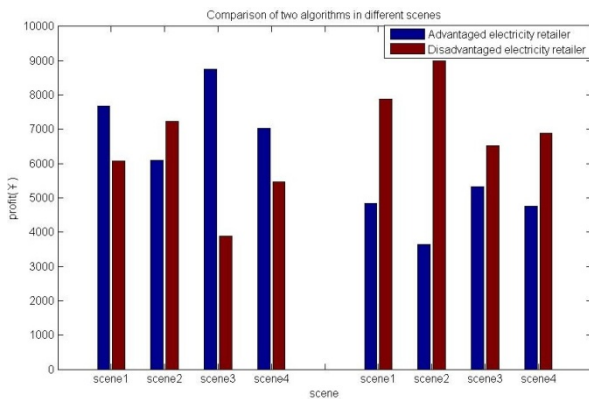

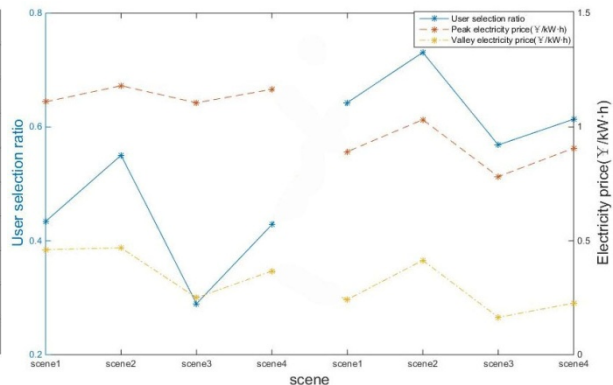Figure 3. Comparison of two optimization algorithms for retailers' income

Figure 4. Comparison of two optimization algorithms for disadvantage retailers' market share and peak and valley electricity prices

Observing FIG. 3, it can be seen that in the multi-objective optimization algorithm, The income of advantaged electricity retailer in scenarios 1, 3, and 4 are greater, Only in Scenario 2, the inferior retailer earns more than the superior one. In the single-target algorithm, the disadvantaged retailer have all gained more profits. Comparing the results of the two algorithms, the multi-objective optimization algorithm is more in line with the actual situation.

In FIG. 4, the market share in each scenario of single-objective optimization is significantly higher than the result of multi-objective optimization, and the market share of its inferior electricity sellers is more than 50%. The peak-valley electricity price of single-objective optimization is generally lower than multi-objective optimization. This indicates that the result of single-objective optimization is that the inferior electricity supplier deliberately lowers the electricity price, thereby obtaining a high market share.

5. Conclusion

(1) Single-objective optimization only starts from itself, ignoring the reaction of the opponent, and the results deviate from the facts.

(2) The strategy obtained by single-objective optimization is single, and the multi-objective algorithm can obtain the strategy set for the electricity supplier to choose.

(3) The single-objective optimization cannot reflect the trend of income changes brought by the adjustment of electricity prices.

(4) Single-objective optimization is not as good as multi-objective optimization in responding to opponent strategy changes.

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