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A Multi-Participant Benefit Maximization Model and Strategy Optimization in Market Transactions Incorporating Game Theory

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ABSTRACT
This topic discusses the problem of maximizing the interests of multiple participants in the trading market based on game theory. Taking the electric power market as a study case, an interest maximization model of multi-party trading strategy in the electric power market is constructed, and the ADMM algorithm is used to solve the model. The rationality and effectiveness of the described model are verified through experimental analysis and arithmetic simulation. Compared with other algorithms, the ADMM algorithm in this paper has a faster convergence speed, and the benefits of the grid company, the benefits of the new entities and the benefits of the users under different numbers of users are all closest to the ideal Nash equilibrium state, which shows the superiority of the ADMM algorithm in this paper. The constructed model is used to solve the conflict of interests among the grid company, new entities and users, and the existence and uniqueness of the game equilibrium is proved through analysis and derivation, and has good convergence results. After the optimization of the strategy in this paper, the revenue of the added entity increases by 6.76%, the power purchase cost of the users decreases by 10.29%, and the consumption surplus increases by 4.50%. Through price-guided output, the load curve is realized to shift peaks and fill valleys, so that the grid company, the added entities and the users get higher benefits.

Keywords: game theory, ADMM, benefit maximization, arithmetic simulation, multi-party trading

1. Introduction

Under the guidance of the deepening reform of the world industry and the national policy, how can the game parties obtain their own maximum benefits in the market multi-party transactions [1]? The market transaction model is not only a purely technical model, but also a model of the economic field

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based on the Internet environment, which has its own economic attributes, such as information asymmetry, game equilibrium, incentive compatibility, economic efficiency, and economic and technical characteristics of the market structure. Choosing what kind of theoretical tools can both meet the technical needs of market transaction models and effectively realize their economic attributes is the key to establishing efficient and practical market transaction models [2-4]. According to the characteristics of the market transaction model and the analysis of several typical market transaction mechanisms, it can be seen that game theory and information economics are the core theoretical tools for realizing various economic attributes of the transaction model, and they have an important role in revealing the transaction logic of the market transaction and the law of micro market behavior [5-7].

Game theory studies the decision-making and the equilibrium problem of such decision-making when the behavior of the decision-making subject occurs in direct interaction, while information economics mainly studies the economic phenomenon of information and its movement and change characteristics, such as the economic role, cost, value and economic effect of information [8-9]. Information has special importance in allocating economic resources, coordinating transactions and negotiations between actors, and affecting the welfare of the economy and society, and at the same time, it runs through the game theory and information economics, making game theory and information economics inseparable [10-11]. In essence, information economics is the application of asymmetric information game theory in economics. The main difference between the two is that, for a given information structure, game theory studies what are the possible equilibrium outcomes, while information economics studies what are the optimal contractual arrangements [12-13]. In the market transaction model, market attributes such as market competition and efficiency equilibrium can be effectively portrayed through game theory, while information economics reveals the characteristics of the economic behavior of market players under information asymmetry from the perspectives of information transmission and coordination of market resource allocation [14-15].

In the market economy, the willingness of the parties involved in the transaction to maximize their interests can only be regulated and guided to the channel of improving efficiency and promoting economic development through competition. And the actions of the participating parties are decisions made from the information provided by the market [16-17]. Information plays an important role in allocating economic resources, coordinating transactions and negotiations between actors, and influencing the welfare of the economy and society. In fact the acquisition, measurement and processing of information is the basis and foundation of all decision making whether in market transactions or in other applications of complex systems [18-19]. In the market transaction model incorporating game theory, the information and the value of the amount of information responded to by the market are particularly important as they have a significant impact on the success and failure, efficiency and quality of the transaction, as well as directly or indirectly affecting the benefits and utility of the parties involved in the transaction [20-22].

This paper takes the multi-party transaction in the electricity market as a research sample, and after analyzing the transaction mode and price mechanism of the electricity market, it integrates the game theory and realizes the construction of the multi-party benefit maximization model in the electricity market by establishing the user benefit model, the new entity benefit model and the grid company benefit model. The ADMM algorithm is used to solve the Nash equilibrium of the constructed game model. On this basis, a comparison algorithm is selected to analyze the convergence effect of the ADMM algorithm, explore the benefits of the grid company, the benefits of the new entities and the benefits of the users under different numbers of users, and evaluate the performance of the ADMM algorithm. After that, a power system is taken as the research object, and the constructed model is used to solve the iterative optimization results of the game of the three participants, and the optimization results of each participant are discussed to explore the benefit enhancement of the optimization strategy of this paper for the three participants in the trading market.

2. A game model for maximizing the interests of multiple parties in market transactions

Game theory is a branch of applied mathematics that is widely used to study the mathematical modeling of strategic strategies between rational players. The focus of game theory is the game of interaction between rational players, and the key is to study the optimal decisions of the players. At present, with the advancement of the reform process of the diversification of power market players, the market-oriented reform has brought the power industry into a completely new competitive environment, and this paper takes the multi-party transaction in the power market as an example, and integrates game theory to construct a benefit maximization model. Firstly, the transaction mechanism of the power market is introduced, and then the multi-party benefit maximization model is constructed and solved.

2.1. Electricity market trading mechanism

2.1.1. Transaction models. At present, China's electricity market mainly involves two parts: the wholesale market and the retail market. According to their own needs, market trading entities carry out independent bilateral transactions or centralized transactions in the wholesale market or retail market, and rely on the auxiliary services market mechanism to ensure the stability and balance of the power system transmission of electricity. The power market transaction model is shown in Figure 1.

In the wholesale market, power suppliers generally act as the main body of power generation and sales, and usually enter into power purchase contracts with power retailers and large power users. The large power users can cross over the power retailer's power sales link and trade directly with the power suppliers in the wholesale market, thus obtaining a lower power purchase price than that of the general group of power users. When the electricity transactions concluded in the market are delivered to the customers through the transmission and distribution networks, the electricity suppliers pay the transmission and distribution companies over-the-grid and grid connection fees according to their access capacity, and the costs incurred are shared by the customers' electricity bills.

In the retail market, the electricity retailer acts as an electricity sales center for market transactions, enters into contractual agreements on electricity with small groups of electricity users, and participates in wholesale market transactions as an agent. The retailer sets the retail price to provide electricity to the lower tier customers based on the trading result, and thus obtains higher revenue through the difference between the wholesale price and the retail price of electricity.

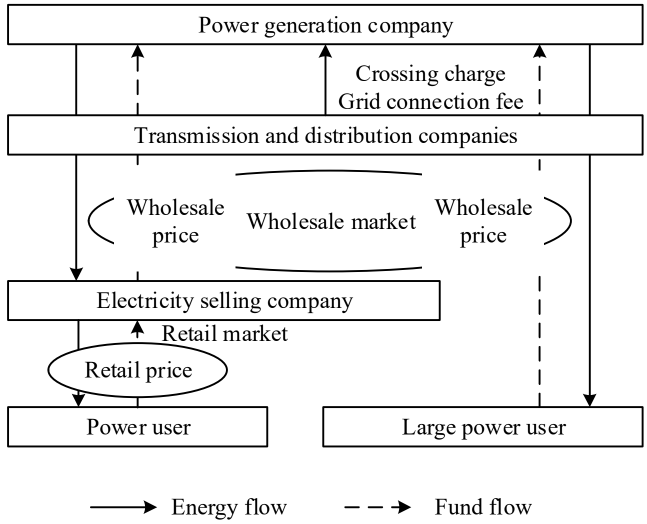


Fig. 1. China's electricity market trading model

2.1.2. Price mechanisms. In view of the transaction situation in China's electricity market, two main electricity price formation mechanisms have been formed, namely the wholesale market and the retail market, and the characteristics of the two electricity price mechanisms in the market are analyzed as follows.

Electricity price formation mechanism in the wholesale market. The current tariff mechanism in the wholesale electricity market is the uniform clearing price mechanism (MCP) mechanism, which means that under certain constraints, the supply side of the electric energy will form a supply curve according to the declared price difference in descending order, and the demand side will form a demand curve according to the declared price difference in descending order, and the intersection of the two curves will be the uniform clearing price difference. In the market where the unified clearing mechanism is implemented, no matter how high or low the price difference is declared by the market players, as long as the bid is awarded, the settlement will be made according to the unified clearing price difference.

Under the MCP mechanism, the generating units of the electricity suppliers in the electricity market will declare their prices according to their marginal costs, so that the market clearing results can follow the constraints of the security of the electricity system, thus realizing efficient and reliable transactions in the electricity market.

Retail market price formation mechanism. The retail electricity market is mainly for electricity retailers and small users in the electricity market, and the transaction price is generally determined by a contract signed after negotiation between the two parties. Electricity retailers generally have two methods of pricing retail electricity:① bottom-up pricing, i.e., pricing determined by stranded costs, transmission costs, and market-based charges for electricity reflecting changes in the hourly spot price, which is applicable to the recovery of stranded costs in a competitive market. ② A top-down pricing methodology, in which retail prices are fixed near historical highs until stranded costs are recovered, until stranded costs are fully recovered.

2.2. Game theory and Nash equilibrium

2.2.1. Game theory. Game theory is an effective theory for choosing optimal strategies in a competitive environment. Among them, non-cooperative game means that the parties of the game do not communicate with each other and choose their own strategies independently of each other, and their own interests not only depend on their own strategy choices, but also have the influence of the behaviors generated by other strategic parties in the environment. Participants strive to achieve the best results based on their own judgment of the surrounding environment.

Assuming that Y is the power price strategy of the parties to the game, each party to the game independently selects the best trading strategy, each party's choice depends on the choice of all the parties to the game, and ultimately meets the requirements of the Nash equilibrium, that is to say, regardless of which party will not change the direction of their own party's strategy, and also needs to be elaborated is not the best overall profitability for all aspects of the trade in this equilibrium situation.

The three elements of the game G are participants, strategy and utility.

1) Participants: Participants are the main body of the game, the decision-maker, usually with $N = 1, 2, \ldots, n$, to represent a game with n participants. In addition to the physical game participants, in a particular scenario, you can set up a virtual game party to help understand the problem.

2) Strategies: Strategies are the actions available to the participants in a game when making decisions, all of which form a combination of strategies. This can be further categorized into pure strategies and mixed strategies. Generally, S_i is used to represent the ith participant's strategy, and $S = \{S_1, S_2, \cdots, S_n\}$ is used to represent the set of strategies of all participants.

3) Utility: utility refers to the benefit received by a participant under a particular strategy combination, and in the case of different strategy combinations, participants have a corresponding utility value. The set of utilities for all participants is generally denoted by $u = \{u_1, u_2, \ldots, u_n\}$.

Therefore, a typical game model in general can be expressed in the form of set representation as:

$$G = \{N, S_1, S_2, \cdots, S_n, u_1, u_2, \cdots u_n\} \tag{1}$$

2.2.2. Nash equilibrium. Equilibrium is a very important definition in adversarial theory, equilibrium is balance, and in economics, its mainly about the constant relationship between quantities. The key element of confrontation theory is to find the Nash equilibrium. The adversarial process is an important reasoning process and is essentially a part of finding the Nash equilibrium. With the help of the Nash equilibrium definition it is possible to study and analyze the choice of methods in the confrontation and the outcome of the confrontation for each of the confronting parties in a non-cooperative confrontation.

Nash equilibrium means that no matter which party's tariff changes, each adversary will not change its tariff method voluntarily, thus maximizing the profit. To ensure the Nash equilibrium, the fitness function can be listed as follows:

$$\Delta w_i = w_i(p^*) - w_i(p) \quad i \in (1, 2, \mathrm{L}, n + m + 1) \tag{2}$$

where: w_i denotes the payoff of game party i, p' and p denote different combinations of tariff strategies of game parties. The Nash equilibrium is reached when Δw_i is constant equal to 0.

2.3. Game Strategies and Trading Rules

The game problem described in this chapter is a pure strategy Nash equilibrium, where the game strategy of the added entity m at time k is the price of the electricity it sells p_m^k, and the thesis assumes that the electricity market imposes an upper $p_{\max}$ and a lower $p_{\min}$ limit on the price of electricity, both in yuan/$\mathrm{kW} \cdot \mathrm{h}$. The game strategy of the grid company is the tariffs charged for the delivery of electricity to the customers and the service charges charged for absorbing the excess electricity of the added entity, and the coefficients of the service charges are denoted by as.

Transaction rules: first of all, the user in accordance with the geographical proximity, give priority to the selection of close and low price of the power supply side, the multi-electricity new entity after being selected after the remaining power and $U_{i0}^2(1-\alpha)/R_{i0}$ for comparison, if greater than

$U_{i0}^2(1-\alpha)/R_{i0}$, then the remaining power will be uploaded to the grid company, if it is less than $U_{i0}^2(1-\alpha)/R_{i0}$, then it will be counted as abandonment of light and wind power loss, and counted as the cost of the new entity, with a coefficient of α expressed in units of yuan /$\mathrm{kW}\cdot\mathrm{h}$, until traversing the all multi-electricity added entities, if at this point the user's power demand has not been met, the grid company provides the user's shortage of power. The flow of electricity during the transaction process is shown in Fig. 2, where the arrow direction indicates the possible flow of electricity during the transaction process.

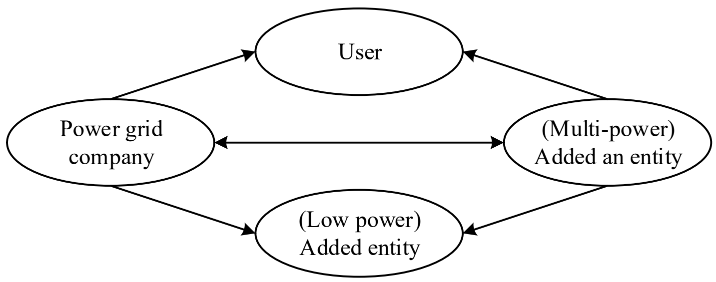


Fig. 2. Electricity flows of power trading rules

2.4. Multi-Benefit Maximization Model

A multi-party benefit maximization model is a function that maximizes the gains obtained by the game participants corresponding to any one strategy. Obviously, there is an interlocking process between the game parties in the transaction process, and the game parties need to consider the strategy choices of other transaction participants in the process of maximizing their own returns. In this paper, the grid company, the new entity of the two revenue model is attributed to the difference between revenue and cost, the user's revenue model is mainly considered to adopt the user's own electricity demand is satisfied in the case of the least expenditure costs strategy.

2.4.1. User Benefits Model. Incorporating users' electricity consumption behavior and transaction strategies into the grid market can avoid the shortage of power output brought about by the inaccuracy of power load forecasting, thus improving the level of fine management of electric energy. Among them, the direct participation of large users in market transactions, in addition to fundamentally changing the nature of the passive power recipient, but also directly enrich the number of market players and improve the market activity.

The utility function of the user mainly involves the cost, power quality and service level satisfaction, etc. This paper takes whether the user's demand is satisfied as the evaluation index of the user's utility, and obtains the user's trading strategy based on the principle of "satisfy self-consumption, and the surplus is connected to the Internet".

Assuming that each power cycle consists of k time period, this paper assumes that $k=24$, user $n(n\in N_n)$ power consumption can be expressed as D_n^k. Then the power consumption distribution matrix of all users can be expressed:

$$\mathbf{D}=\begin{bmatrix} D_1^1 & D_1^2 & \cdots & D_1^k \\ D_2^1 & D_2^2 & \cdots & D_2^k \\ \vdots & \vdots & & \vdots \\ D_n^1 & D_n^2 & \cdots & D_n^k \end{bmatrix} \tag{3}$$

Assuming that the price matrices of grid company S_o and added entity m are $p_0=[p_0^1,p_0^2,p_0^3,\cdots,p_0^k]$ and $p_m=[p_m^1,p_m^2,p_m^3,\cdots,p_m^k]$, respectively, in the electricity consumption cycle, which satisfy $p_0^k \in (p_0^{\min}, p_0^{\max})$ and $p_m^k \in (p_m^{\min}, p_m^{\max})$, respectively, and that user n chooses the electricity supplier based on the high and low electricity prices and the geographical proximity of the user, the electricity price of the user is determined by the following equation.

$$p_n^k = \begin{cases} p_0^k, & p_0^k < p_m^k \ \& \ l_n \in l_0 \\ p_m^k, & p_0^k \geq p_m^k \ \& \ l_n \in l_m \end{cases} \tag{4}$$

where: I_0 denotes the set of power supply ranges of the grid company, and it is assumed in this paper that grid company S_0 is located in the load center. l_m denotes the set of supply ranges of the added entity m.

The payment cost of user n at time k is $\Phi_n^k = p_n^k \cdot D_n^k$, then the payment matrix of the user can be expressed as:

$$\Phi = \begin{bmatrix} \Phi_1^1 & \Phi_1^2 & \cdots & \Phi_1^k \\ \Phi_2^1 & \Phi_2^2 & \cdots & \Phi_2^k \\ \vdots & \vdots & & \vdots \\ \Phi_n^1 & \Phi_n^2 & \cdots & \Phi_n^k \end{bmatrix} \tag{5}$$

In this paper, we assume that the expected range of power D_n^k demanded by user n per unit time k is $D_n^k \in (D_n^{\min}, D_n^{\max})$ and define y_n^k as the user's utility.

$$y_n^k = \beta_D \cdot D_n^k \tag{6}$$

where: β_b is a function of the power demanded by the user, taking the value 1 in the power expectation range and 0 outside the expectation range.

The utility matrix for all users is:

$$Y_n = \begin{bmatrix} Y_1^1, Y_1^2, Y_1^3, \cdots, Y_1^k \\ Y_2^1, Y_2^2, Y_2^3, \cdots, Y_2^k \\ \vdots \\ Y_n^1, Y_n^2, Y_n^3, \cdots, Y_n^k \end{bmatrix} \tag{7}$$

The user benefit matrix W_n can be represented by the following equation:

$$W_n = Y_n - \Phi \tag{8}$$

2.4.2. New entity revenue model. The additional entity is a special class of users that can generally satisfy its own power balance due to the presence of DG and energy storage equipment, and when acting as a lesser party, it can be regarded as a simple load user, which does not generate benefits and needs to be supplied with electricity by other supplying parties. When acting as a multipoint party, the power quality has met its own expectations and receives additional remuneration by supplying power to other trading parties to collect tariffs.

In order to simplify the calculation, this paper assumes that all newly added entities are multi-electricity parties, in which user $i(i \in N_n^l)$ chooses the newly added entity as the power supply party and user $j(j \in N_n^S)$ chooses the grid company as the power supply party, and the newly added entity $m(m \in N_1^s)$ delivers the excess electricity to the grid company, assuming that the grid is able to absorb the excess electricity of all newly added entities. The newly added entities decide whether to participate in the transaction at moment k after judging the cost of abandoned light and wind and the revenue from selling electricity.

Assuming that the excess power of the added entity m at time k is $D_m^k \in (D_m^{\min}, D_m^{\max})$, the price of electricity sold by the added entity m to the grid company is p_m^k, and the payment made by the grid company to the added entity m is $\Phi_m^k = p_m^k \cdot D_m^k$. The payment matrix of the grid company is:

$$\overline{\Phi} = \begin{bmatrix} \overline{\Phi}_1^1 & \overline{\Phi}_1^2 & \cdots & \overline{\Phi}_1^k \\ \overline{\Phi}_2^1 & \overline{\Phi}_2^2 & \cdots & \overline{\Phi}_2^k \\ \vdots & \vdots & & \vdots \\ \overline{\Phi}_{N_1^3}^1 & \overline{\Phi}_{N_1^3}^2 & \cdots & \overline{\Phi}_{N_1^3}^k \end{bmatrix} \tag{9}$$

The benefit matrix for the (multi-electric) added entity is shown in the following equation:

$$Y_m = \Phi \cdot A_n^I + \overline{\Phi} \tag{10}$$

where: A_n^I denotes the choice matrix of the user.

The added entity cost mainly refers to the power losses incurred in the process of supplying electricity to the grid company and the user.

The added entity cost matrix is shown in the following equation:

$$C_m = P_n^I + P_I^S \tag{11}$$

In this paper, we define the difference between the revenue and cost of the added entity as the benefit of the added entity, denoted by W_m. The benefit matrix of the added entity is:

$$W_m = Y_m - C_m \tag{12}$$

2.4.3. Grid company revenue model. The grid company is a strong backing for the power supply of the power system, and it can provide power to the system to ensure the power balance of the system when the added entities are scheduling shortages. However, the distance between the grid company and the added entities and the distance with the users is much larger than the distance between the added entities and from the added entities to the users, so its transmission power loss is larger.

The revenue model of the grid company is analogous to the revenue model of the added entity, which can also be defined as the difference between revenues and costs. The grid company's revenues Y_0 are mainly the tariffs charged while delivering power to the customers and the service charges charged when absorbing the excess power from the added entities. In this paper, we assume that the active output of the grid company is infinite. Then:

$$Y_0 = \Phi \cdot A_n^s + a_s \cdot \overline{\Phi} \tag{13}$$

where: A_n^s denotes the choice matrix of the customer, where a_s denotes the cost of service coefficient.

The cost of the grid company C_0 is mainly the operating cost due to power losses in delivering electricity to the customer:

$$C_0 = P_n^S \tag{14}$$

The grid company's revenue matrix W_0 can be expressed in the following equation:

$$W_0 = Y_0 - C_0 \tag{15}$$

2.5. Solving Nash equilibrium based on ADMM

Alternating Direction Multiplier Method (ADMM) is suitable for solving convex optimization decomposable problems, the essence of the algorithm is to transform a complex optimization problem into multiple sub-problems, and then solve each sub-problem individually or in parallel to obtain the global optimization solution, with excellent convergence and robustness.

Suppose the optimization problem is:

$$\begin{aligned} &\min f(x)+g(z) \\ &s.t.\, Ax+Bz=c \end{aligned} \tag{16}$$

Eqs. $x \in R^s, z \in R^n, A \in R^{p\times s}, B \in R^{p\times n}, c \in R^p; f: R^n \to R_o$. x and z denote the independent variables to be optimized.

The augmented Lagrangian function of Eq. (16) can be expressed as:

$$L_\rho(x,y,z)=f(x)+g(z)+y(Ax+Bz-c)+\frac{\rho}{2}\| Ax+Bz-c\|_2^2 \tag{17}$$

where: y is the Lagrange multiplier, $\rho > 0$ is the penalization factor. $\frac{\rho}{2}\| Ax+Bz-c\|_2^2$ is the quadratic penalty term of the augmented Lagrangian function.

In this mathematical optimization problem using ADMM algorithm decomposition optimization steps are as follows:

$$x^{k+1}=\arg\min_x L_\rho(x,z^k,y^k) \tag{18}$$

$$z^{k+1}=\arg\min_z L_\rho(x^{k+1},z,y^k) \tag{19}$$

$$y^{k+1}=y^k+\rho(Ax^{k+1}+Bz^{k+1}-c) \tag{20}$$

To make Eqs. (18)~(20) compact and neat, order $u=\frac{y}{\rho}$ and treat $Ax+Bz=c$ formulations:

$$x^{k+1}=\arg\min_x (f(x)+\frac{\rho}{2}\| Ax+Bz^k-c+u^k\|_2^2) \tag{21}$$

$$z^{k+1}=\arg\min_z (g(z)+\frac{\rho}{2}\| Ax^k+Bz-c+u^k\|_2^2) \tag{22}$$

$$u^{k+1}=u^k+Ax^{k+1}+Bz^{k+1}-c \tag{23}$$

From the above equation, the ADMM algorithm solves the subproblems containing x and z variables alternately in the solution procedure with update delivery, and then replaces the dyadic variables based on the values of the updated variables.

Finally, the independent variables of the augmented Lagrangian function in Eq. (17) are biased:

$$\partial f(x^{k+1})+A^T y^{k+1}+\rho A^T B(z^k-z^{k+1})=0 \tag{24}$$

$$\partial g(z^{k+1})+B^T y^{k+1}=0 \tag{25}$$

This yields the nonoptimal distances corresponding to the pairwise residuals $Ax^{k+1}+Bz^{k+1}-c$ and the original residuals $\rho A^T B(z^{k+1}-z^k)$ as:

$$r_{k+1}=\| Ax^{k+1}+Bz^{k+1}-c\|_2 \tag{26}$$

$$s_{k+1}=\| \rho A^T B(z^{k+1}-z^k)\|_2 \tag{27}$$

and the maximum degree of error between the original problem and the pairwise problem is:

$$\varepsilon^{pn}=\sqrt{N}\varepsilon^{abs} \tag{28}$$

$$\varepsilon^{dual}=\sqrt{N}\varepsilon^{abs} \tag{29}$$

Where: N is the number of variables.

During the iteration process, the algorithm converges to send generation termination when the non-optimal distance is less than or equal to the maximum allowable error.

$$r_{k+1} \le \varepsilon^{pri} \tag{30}$$

$$s_{k+1} \le \varepsilon^{dual} \tag{31}$$

3. Experimental evaluation and analysis

In this chapter, experiments are conducted to evaluate the convergence effect and performance of the ADMM algorithm and a comparative analysis with other algorithms is done.

3.1. Comparison Algorithm

1) GIGA-WoLF algorithm: This is an algorithm that keeps track of two different gradients when updating the strategy, and solves the two major problems of convergence and regret in the game at the same time.The GIGA-WoLF algorithm is a significant improvement on the original WoLF-IGA algorithm, requiring less knowledge and at the same time, since GIGA has the same regret limit for any strategy, updating the strategy using GIGA can ensure that the algorithm has no regret and avoids being lured into choosing strategies that yield lower returns by utilizing specific dynamic strategies.

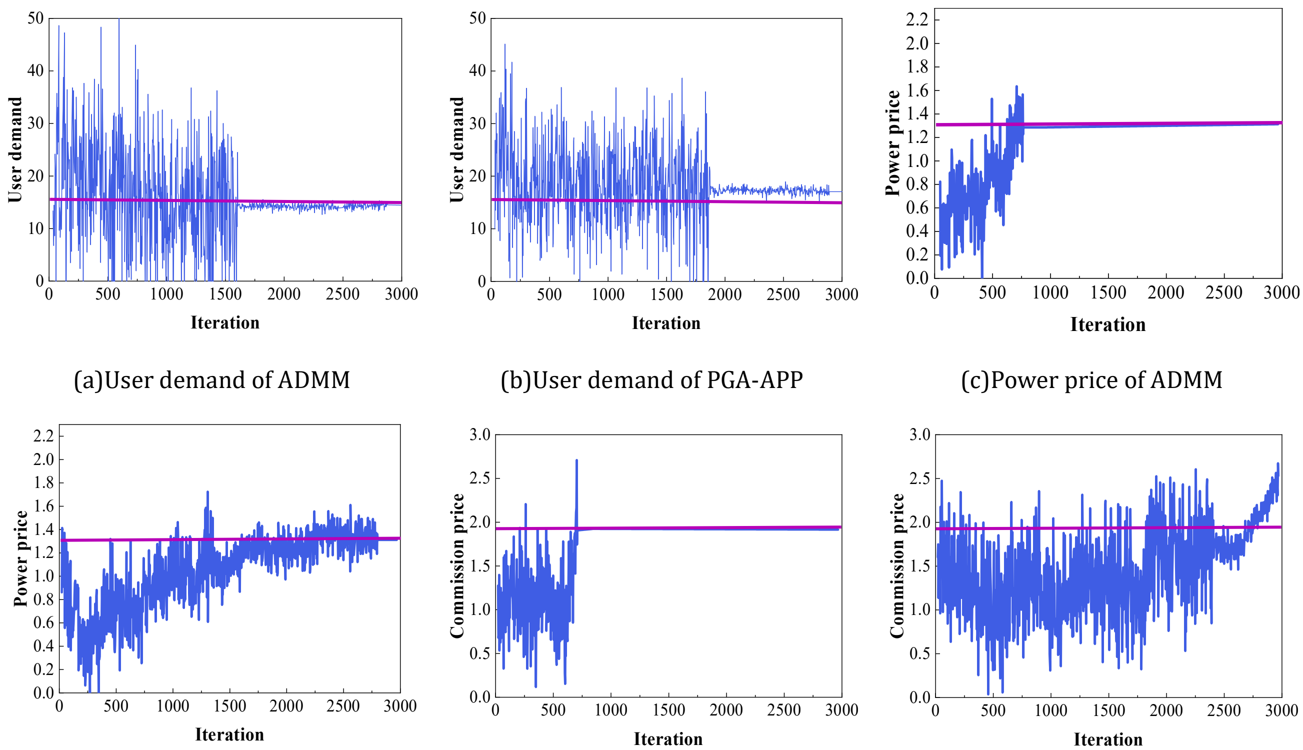
2) PGA-APP algorithm: this algorithm is proposed based on the IGA-PP algorithm for predicting strategy-enhancing gradient ascent, and adjusts its own strategy by predicting other subjects' strategies, rather than their current strategy.

3) Optimal algorithm: this is based on solving the theoretical optimal solution of the algorithm under the complete information of the environment, i.e. the Nash equilibrium point. However, in real life, due to certain condition constraints, it is almost impossible for the market transaction subject to fully access to other participants' state, state and reward information, and can only rely on its own local observation to make actions, which makes it difficult to converge and reach the theoretical optimal solution in the dynamically changing multi-participant system environment. Therefore, the optimal algorithm is only theoretical and is only used for subsequent algorithm performance comparisons.

3.2. Algorithm convergence effect

In this section, the electricity market is simplified to consist of 1 grid company, 3 added entities and 10 users, and the convergence performance of the ADMM algorithm is evaluated in the following. The ADMM algorithm and the PGA-APP algorithm are applied to solve the strategies of the users, the added entities and the grid company, respectively, and the convergence of the algorithms is observed, and the experimental results are shown in Fig. 3, in which the purple line in the subfigure represents the optimal solution of the theoretical Nash equilibrium, and (a) to (f) are the training results of the ADMM algorithm and the PGA-APP algorithm in terms of the users' demand, the price of electricity, and the price of the commissions, respectively.

The PGA-APP as a comparison algorithm converges slowly, and it is difficult for it to adapt quickly to the dynamic environment caused by multi-participant competition. In contrast, as shown in Figs. (a), (c) and (e), the ADMM algorithm greatly accelerates the convergence speed, which is completed in about 1600, 760 and 740 iterations, while the user's demand for electricity, the price of electricity resources of the new entity and the commission price of the grid company all converge to the Nash equilibrium point (purple line).



(a)User demand of ADMM (b)User demand of PGA-APP (c)Power price of ADMM

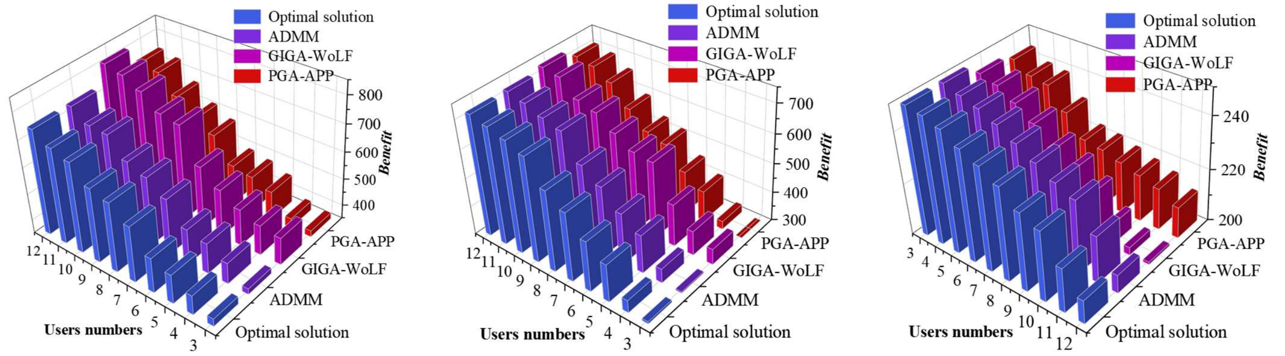
(d)Power price of PGA-APP (e)Commission price of ADMM (f)Commission price of PGA-APP

Fig. 3. The convergence effect of the ADMM algorithm and the PGA-APP algorithm

3.3. ADMM algorithm performance

In order to evaluate the performance of ADMM algorithm, this paper compares and analyzes it with GIGA-WoLF, PGA-APP and optimal algorithms under different number of users. Fig. 4 shows the benefits of different algorithms for all parties in the market under different numbers of users, and (a) to (c) correspond to the distributions of grid company benefits, new entity benefits, and user benefits with the number of users.

In the figure, blue color indicates the theoretical optimal algorithm, and purple color indicates the ADMM algorithm. It is easy to find that the ADMM algorithm is closest to the optimal algorithm in terms of the grid company benefits in Fig. (a), the new entity benefits in Fig. (b), and the user benefits in Fig. (c), i.e., the game of the market parties achieves the Nash equilibrium, and the benefits of the three participants corresponding to the different numbers of users are in the ranges of 400-800, 300~700, and 200-250. 700 and 200~250.Meanwhile, the GIGA-WoLF algorithm denoted in purple and the PGA-APP algorithm denoted in red perform poorly, for example, compared with the optimal algorithm, the GIGA-WoLF algorithm realizes greater benefits for the grid company in Fig. (a) and reduces the benefits of the individual users in Fig. (c), which suggests that the benefits are unbalanced at this time and the whole system is in an unstable state. The above discussion shows the excellent performance of the algorithm proposed in this paper.



(a)Grid company benefit (b)New entity benefit (c)User benefit

Fig. 4. The benefits of different algorithms in different users

4. Example results and analysis

4.1. Example data

Trying to build an accurate model of the electricity market is difficult because the electricity market is an extremely complex system. In this paper, we study a 10^*10km^2 system, which is geographically centered on the grid company, and assume that there are 5 added entities in the system and the number of users is 100.

It is assumed that there is an electrical connection between the users, the added entities and the grid company, and the distance of the electrical is approximated to the distance between the two, and it is set that the line voltage of the lines are all 12.66 kV, the resistance is 0.20 Ω, the cost coefficient of the added entities for light and wind abandonment is 0.3 yuan/kW·h, the cost coefficient of the service charged by the grid company is 0.15 yuan/kW·h, and the network loss penalty factor of 0.8 yuan/kW·h.

4.2. Analysis of results

4.2.1. Game Iterative Optimization Results. The iterative process of optimizing the total returns of the three participants is shown in Fig. 5, which shows that the returns change faster in the beginning stage and gradually converge and reach stability after 50 iterations, reflecting the game process among the three participants. The process of the grid company, as the leader of the market transaction, making its own gain gradually rise reflects its leadership position in the master-slave game. When the iteration converges and reaches the Nash equilibrium, it indicates that the three players cannot find other strategies to make their returns higher, and the final returns of the grid company, the new entities, and the users are 5904, 5156, and 2008 yuan, respectively.

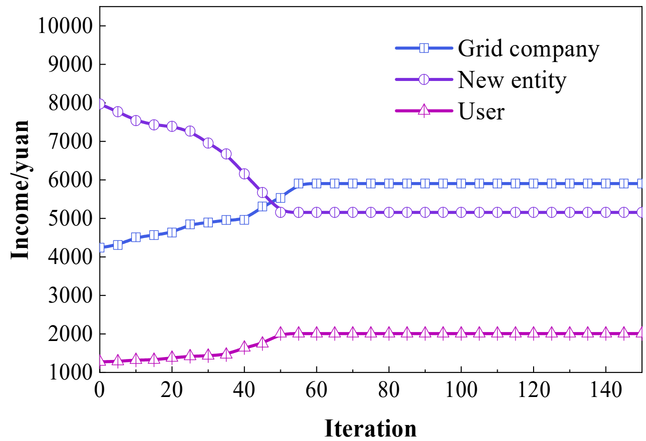


Fig. 5. The optimization iterative process of the total benefits of the three parties

4.2.2. Grid company optimization results. The price strategy of the grid company is shown in Figure 6. Under the set market trading strategy, the grid company's pricing strategy is lower than the higher grid's time-of-use tariff (blue symbols) and higher than the new energy feed-in tariff (red symbols), which is favorable to the interests of producers and users in the region. The fluctuation of the grid company's purchase price is small, between 0.35 and 0.60 yuan, and the fluctuation trend of the sale price is similar to the trend of the customer's load, i.e., the sale price is relatively high during the peak hours of the customer's electricity consumption. The grid company sells and purchases power at 13:00-18:00 and 19:00-22:00 with a higher price difference, and it can be inferred that the revenue of electricity is concentrated in these two periods.

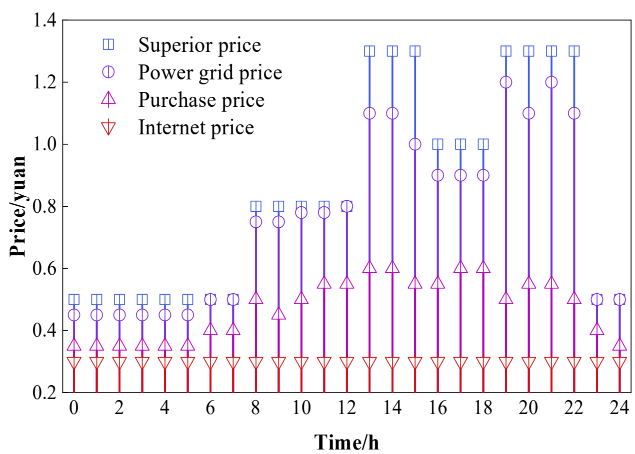


Fig. 6. Grid company price strategy

4.2.3. New Entity Optimization Results. The load curves before and after the optimization of the added entities are shown in Fig. 7. After adopting the optimization strategy in this paper, the peak hours of 11:00-13:00 and 17:00-21:00 are shifted to 0:00-7:00 and 22:00-24:00, and the output loads of the new entities are significantly smoother and less fluctuating than those of the new entities before optimization, reducing the pressure on the energy supply. The benefit of the added entity before optimization was 5,741 yuan, which increased to 6,129 yuan after optimization, an increase of 6.76%.

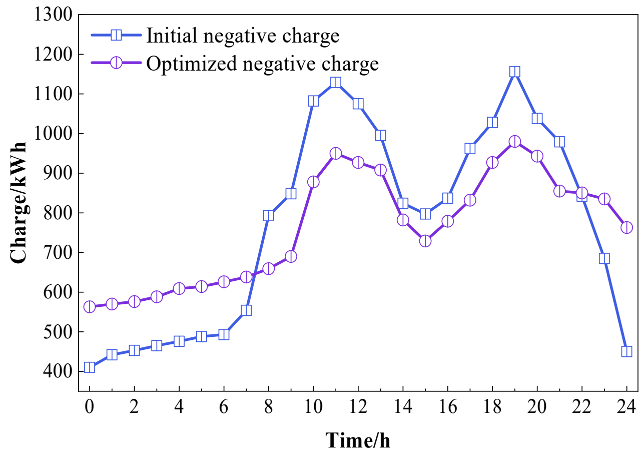


Fig. 7. Load curve before and after optimization of new entity

4.2.4. User optimization results. The load curves before and after the customer's integrated demand response are shown in Figure 8, and the before and after demand response comparisons are shown in Table 1. In order to reduce the cost of electricity consumption during the peak hours of electricity price, the original peak drop of 11:00-13:00 and 18:00-20:00 is shifted to the hours of 0-8:00 and 22:00-24:00, and the electric load is shifted to fill in the valleys, which optimizes the load curve. Relative to the pre-optimization period, the comfort level of electricity consumption decreased by 3.74%. The cost of energy purchase decreased by 10.29%. Consumer surplus increased by 4.50%. Compared with the pre-optimization period, although some comfort is sacrificed, the cost of energy purchased by the users is reduced and the consumer surplus is increased, which balances the economy and comfort of energy use.

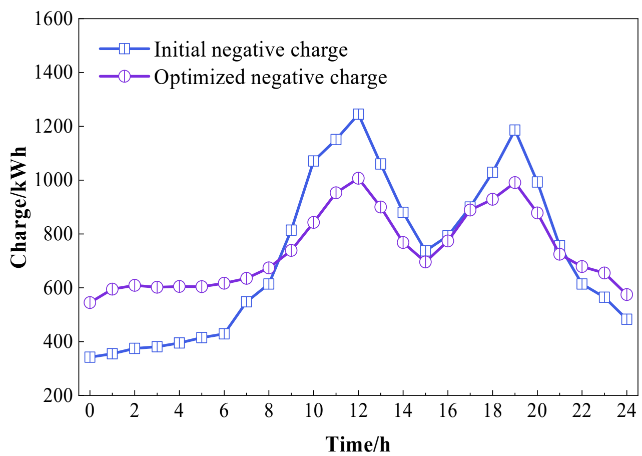


Fig. 8. The load curve of the user's comprehensive demand response

Table 1. The comparison before and after the requirements response(yuan)

	Cost of electric comfort	Purchase cost	Consumer surplus
Preoptimize	10521	4217	2575
After optimization	10127	3783	2691

5. Conclusion

The study introduces game theory into the analysis of multi-party interest maximization strategies in market transactions, starts from electricity market transactions, establishes a game model containing three parties: the grid company, the added entities and the users, and solves the Nash equilibrium by using the ADMM algorithm. The performance of the ADMM algorithm is evaluated through experimental analysis, and case study analysis is carried out. The main results of the study are as follows:

1) Compared with the selected comparison algorithm, the ADMM algorithm in this paper shows faster convergence speed in training, and in the process of measuring the benefits of the grid company, the benefits of the new entities and the benefits of the users, the ADMM algorithm is the closest to the Nash equilibrium effect in the ideal environment, which verifies the good performance of the algorithm.

2) Using the model to solve the conflict of interest between the grid company, the added entities and the users, and obtaining the iterative optimization results of the game of each participant, the proposed strategy enables the grid company to formulate a reasonable price strategy, and through the price-guided output, the output of the added entities is more stable, and the benefits are increased by 6.76%. At the same time, the benefits of the users also gained growth, and their power purchase cost decreased by 10.29% and their consumption surplus increased by 4.50%. It shows that the proposed strategy has superior feasibility.

3) Against the background of deepening power market reform, the strategy proposed in this paper has certain practical significance, providing useful ideas for optimizing the pricing mechanism, tapping the load-side response capability, and improving the level of power energy consumption. As the interaction of market players becomes more and more obvious, we will continue to enrich the market players, extend the model and related conclusions, and carry out research on “multi-master multi-slave” market transactions in the future.

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