Electric Energy Trading Mechanism of Distributed Electric Vehicles in Smart Grid

Chunlin Hu
Faculty of Electronic and Information Engineering
Xi'an Jiaotong University
Xian 710049, China
hucl0918@stu.xjtu.edu.cn

Dou An
Faculty of Electronic and Information Engineering and the MOE Key Laboratory for Intelligent Networks and Network Security
Xi'an Jiaotong University
Xian 710049, China
douan2017@xjtu.edu.cn

2023 38th Youth Academic Annual Conference of Chinese Association of Automation (YAC) | 979-8-3503-0363-6/23/$31.00 ©2023 IEEE | DOI: 10.1109/YAC59482.2023.10401661

***Abstract*—With the continuous development of the smart grid and the increasing number of electric vehicles (EVs), the power transaction in the smart grid has become increasingly important in our daily life. This paper studies the distributed trading mechanism of electric vehicle energy in a smart grid. First, a non-cooperative game model is established among EV users. Each user can buy and sell power to both the central grid and other EV users. EV owners may act as buyers or sellers in the transaction according to their power availability. Next, this paper calculates the optimal utility function for EV users and obtains the optimal decision. The expression of the Nash equilibrium solution and the optimal user utility function are given. Then the efficiency of Nash equilibrium is analyzed. Finally, demand response management is carried out under the model. This paper designs two groups of comparative experiments. The first experiment compared daily electricity consumption and electricity charges of users before and after demand response management. The second experiment showed how the sum of electricity bills changed with the number of users who don't change their habits.**

Keywords—electricity transaction; non-cooperative game; Nash equilibrium; demand response management

I. INTRODUCTION

Smart grid is a new type of modern power grid, which combines a power network and an information network. The advantages of a smart grid include real-time information interaction, flexible data upload, access to new energy, and a flexible demand response management mechanism. The current smart grid is highly marketable. Pricing strategy plays an important role in the demand response management of the smart grid. It's the basis of demand response management. The current popular pricing strategies include ladder pricing, peak pricing, and time-sharing pricing. A smart grid adds many new elements based on a traditional power grid. Song Yu et al. applied intelligent panorama technology to a smart power grid for design planning and data integration [1]. Qu Shuihua et al. added 5G technology to the smart power grid. The time accuracy and the reduced end-to-end delay are improved obviously [2]. From the perspective of environmental protection, Duan Kai et al. focused on the design of smart grid architecture and promoted the low-carbon development of smart grids [3]. Sun Bo et al. established a joint optimal scheduling model for the EV demand response of the wind storage hybrid system. They obtained a joint scheduling strategy with maximum benefits [4].

This paper studies the distributed trading mechanism of EV energy in the smart grid. The main work of this paper is as follows:

- We establish a non-cooperative game model among electric vehicle users.
- We calculate the optimal utility function for EV users, obtain the optimal decision, and analyze the non-cooperative game under this model.

The rest of this paper is organized as follows. In Section II, we establish a non-cooperative game model and give the expression of the optimal utility function. In Section III, we consider demand response management and develop a power adjustment mechanism. In Section IV, we design two groups of comparative experiments from different angles. And finally, we conclude our paper in Section V.

II. NON-COOPERATIVE GAME BETWEEN ELECTRIC VEHICLE USERS

A. The Non-cooperative Game between Sellers

This chapter establishes an electric energy trading model. The research scenarios of this model include electric energy surplus and electric energy shortage of electric vehicle users.

We define I as the set of buyers and J as the set of sellers. For each seller $\forall j \in J$, we use the following utility function.

$$U_i(C_i, C_{-i}) = \alpha * E(C_j - C_b) \tag{1}$$

where the buyer's utility function $U_i(C_i, C_{-i})$ is a concave, continuous and monotone function. C_j is defined as the unit price submitted by the seller to the buyer. C_s and C_b are respectively the selling price and purchase price of the central power grid. E is the excess electric energy generated by seller j. α is a constant coefficient, which is related to the satisfaction requirements of each EV user.

We define the sellers' optimal utility function as follows:

$$B_j(C_{-j}) = \arg\max U_j(C_j, C_{-j}) \tag{2}$$

The result of the game reaching the Nash equilibrium is denoted as

$$C_j^* = B_j(C_{-j}^*) \tag{3}$$

The expression of the unique Nash equilibrium solution for the non-cooperative game between sellers is

$$C_j^* = C_b \frac{2k_1 - 1}{k_1 - 1} \tag{4}$$

where k_1 is the seller's quantity.

In this paper, η is used to represent the efficiency of Nash equilibrium, and its specific expression is

$$\eta = \frac{C_b}{(C_s - C_b)} * \frac{k}{k-1} \tag{5}$$

B. The Non-cooperative Game between Buyers

Like sellers, for each buyer $\forall i \in I$, we use the following utility function:

$$U_i(C_i, C_{-i}) = \mu * (C_s - C_i) \tag{6}$$

where μ is a constant coefficient, which is related to the satisfaction requirements of each user.

The Nash equilibrium solution of the non-cooperative game between buyers is

$$C_i^* = C_s \frac{k_2 - 1}{2k_2 - 1} \tag{7}$$

where k_2 is the buyers' quantity.

The Nash equilibrium efficiency expression of the non-cooperative game between buyers is

$$\eta = \frac{C_s}{(C_s - C_b)} * \frac{k}{2k-1} \tag{8}$$

III. Establishment and Analysis of Demand Response Management Model

In the demand response management model, we use the Starkelberg game framework to analyze the two-level demand response management process between the user and the power supplier. In the game, we set the power supplier as the leader. The leader makes his decision for the follower, the electric vehicle user, namely the real-time price signal. Users, on the other hand, use the price signals issued by the leader to optimize their load demand allocation. Therefore, the whole game process can be viewed as a power price game between the various power suppliers. The power supplier sets its electricity price according to the demand of customers at each time and the price of other power suppliers. Users will not participate in the whole process of the game, but will only change their inherent electricity consumption mode through the real-time price signal released by the power supplier, so as to maximize their utility function. The demand response management model in smart grid electricity transactions is shown in Fig 1.

The process of demand response management is as follows:

1)The power supplier sets the real-time power price and informs the user.

2)The power supplier sets the real-time power price and informs the user.

3)The power supplier updates the real-time electricity price according to the electricity consumption policy received by the user.

Then, repeat from steps 1) to 3) until the game reaches a Nash equilibrium.

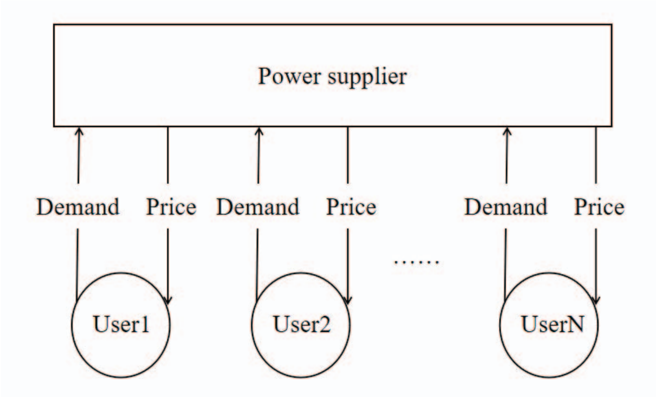

Fig 1 Demand response management model

A. Model of Users

In this paper, the following logarithmic function is used to represent the user's utility function.

$$U_n(l_{n,k}^h) = \gamma_n \sum_{k \in K} \ln(\beta_n + C_n l_{n,k}^h) \tag{9}$$

where $\gamma_n > 0$, $\beta_n \geq 1$, $C_n > 0$ and they're all constant coefficients.

Customers have the highest electricity budget for each time period. In this paper, the Lagrange equation is constructed with the budget value as the constraint condition, and the user's choice of electricity consumption strategy under the independent state is obtained. The Lagrange equation is

$$\max U_n(l_{n,k}^h)$$
$$s.t. \begin{cases} \sum_{k \in K} p_k l_{n,k}^h \\ l_{n,k}^h \geq 0 \end{cases} \tag{10}$$

where p_k represents the real-time power price provided by the power supplier k. B_n is the maximum electricity bill that user n can afford for each period of time. At this point, each user does not know the decisions of other users, so each user's decisions can be viewed as made independently. Therefore, at this stage, the user does not need to consider using more power than the maximum power supply from the supplier.

We assume that there are N users and 4 power suppliers in the demand response management system. The optimization problem can be expressed as

$$\max \gamma_n \sum_{k=4} \ln(\beta_n + C_n l_{n,k}^h)$$
$$s.t. \begin{cases} p_1 l_{n,1}^h + p_2 l_{n,2}^h + p_3 l_{n,3}^h + p_4 l_{n,4}^h \le B_n \\ l_{n,1}^h, l_{n,2}^h, l_{n,3}^h, l_{n,4}^h \ge 0 \end{cases} \tag{11}$$

It is assumed that $\lambda_{n,1}$, $\lambda_{n,2}$, $\lambda_{n,3}$, $\lambda_{n,4}$ are Lagrange multipliers. The optimization problem of inequality constraint can be expressed by Lagrange function as

$$\begin{aligned} L_n = \gamma_n \sum_{k=1}^{4} \ln(\beta_n + C_n l_{n,k}^h) - \lambda_{n,1}(\sum_{k=1}^{4} p_k l_{n,k}^h - B_n) \\ + \lambda_{n,2} l_{n,1} + \lambda_{n,3} l_{n,2} + \lambda_{n,4} l_{n,3} + \lambda_{n,5} l_{n,4} \end{aligned} \tag{12}$$

The KKT condition is

$$\begin{cases} \lambda_{n,1}(\sum_{k=1}^{4} p_k l_{n,k}^h - B_n) = 0 \\ \lambda_{n,2} l_{n,1} = 0 \\ \lambda_{n,3} l_{n,2} = 0 \\ \lambda_{n,4} l_{n,3} = 0 \\ \lambda_{n,5} l_{n,4} = 0 \\ \lambda_{n,1} > 0 \\ \lambda_{n,2}, \lambda_{n,3}, \lambda_{n,4}, \lambda_{n,5} \ge 0 \end{cases} \tag{13}$$

When the utility function reaches its maximum value, the first derivative of equation (12) is equal to zero. Finally, we can obtain

$$l_{n,k}^h = \frac{B_n + \sum_{k=1}^{4} p_k \beta_n}{4 p_k C_n} - \frac{\beta_n}{C_n} \tag{14}$$

Therefore, according to Equation (14), the user's demand for each power supplier can be extended to the scenario where there are K power suppliers, and the optimal demand for each power supplier is as follows:

$$l_{n,k}^h = \frac{B_n + \sum_{k=1}^{4} p_k \beta_n}{K p_k C_n} - \frac{\beta_n}{C_n} \tag{15}$$

B. Model of the Power Suppliers

The utility function of the power supplier can be expressed as

$$U_k(p_k, p_{-k}) = p_k \sum_{n \in N} l_{n,k}^h \tag{16}$$

where p_{-k} represents the real-time price of power supplied by other power suppliers except k.

Each power supplier cannot supply more electricity than its maximum capacity in each period. The optimization function of the power supply can be expressed as

$$\max U_k(p_k, p_{-k})$$
$$s.t. \begin{cases} \sum_{n \in N} l_{n,k}^h \le G_k \\ p_k > 0, \forall k \in K \end{cases} \tag{17}$$

The Lagrange function is

$$L_k = p_k \sum_{n \in N} l_{n,k}^h - \lambda_k (\sum_{n \in N} l_{n,k}^h - G_k) \tag{18}$$

When the supplier gets the best price, $\frac{\partial L_k}{\partial p_k} = 0$,

$$(K-1) Z p_k^2 - \lambda_k [B_k + Z(\sum_{u \in K, u \ne k} p_u)] = 0 \tag{19}$$

where $Z = \sum_{n \in N} \frac{\beta_n}{C_n}$, $B = \sum_{n \in N} B_n$.

According to (17), we can obtain

$$p_k = \frac{B + Z(\sum_{u \in K, u \ne k} p_u)}{Z(k-1) + K G_k} \tag{20}$$

The calculation of the supplier price is converted into a function of the capacity of each supplier. We have

$$p_k = \frac{B}{G_k + Z} \left(\frac{1}{K - \sum_{k \in K} \frac{Z}{G_k + Z}} \right) \tag{21}$$

Finally, we can obtain

$$l_{n,k}^{h^*} = \frac{C_n B_n^h + \sum_{k=1}^{K} \frac{\beta_n}{C_n} \frac{B_n^h}{G_k + Z} \left(\frac{1}{K - \sum_{k \in K} \frac{Z}{G_k + Z}} \right)}{C_n K \frac{B_n^h}{G_k + Z} \left(\frac{1}{K - \sum_{k \in K} \frac{Z}{G_k + Z}} \right)} - \frac{\beta_n}{C_n} \tag{22}$$

where $l_{n,k}^{h^*}$ is the real-time electricity price given by each user from a known power supplier.

IV. Experiment

A. Process of Algorithmic

In this paper, the algorithm flow of demand response management for electric vehicle users is as shown in Fig 2.

First, we need to figure out the optimal power consumption strategy in the users' independent state; Next, Summarize the power consumption strategies independently calculated by users to ensure that the sum of all users' power consumption does not exceed the maximum power supply value of the power supplier; Finally, obtain the final optimal power consumption decision of all users.

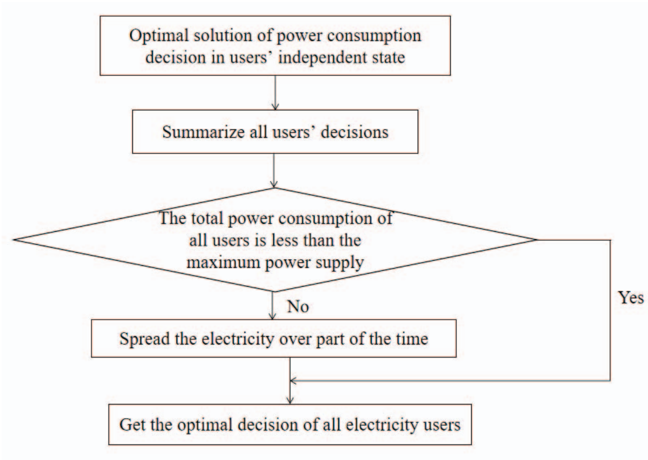

Fig 2 Algorithmic flow of demand response management

B. Experimental Environment

In this paper, we set the number of users in demand response management at 10. In the smart grid electricity transaction, the unit price of electricity charged at night is lower. Therefore, we set the price of electricity from 22:00 to 8:00 the next day $C_{h1} = ah_1 * l_{n,k}^h * l_{n,k}^h + bh_1 * l_{n,k}^h$, and that at the other time $C_{h2} = ah_2 * l_{n,k}^h * l_{n,k}^h + bh_2 * l_{n,k}^h$. Where $ah_1 = bh_1 = 0.03$, $ah_2 = bh_2 = 0.05$. The maximum tariff budget ($) for each period is

$$B_n = [5,5,5,5,5,5,5,5,5,5,10,10,10,\\ 10,10,20,25,25,22,22,22,20,12,10]$$

We assume that the number of power suppliers is set to 3, and the maximum power supply value (Kwh) of each power supplier in each period is as follows

$$G_{k1} = [6,6,5,5,6,6,7,5,6,6,6,6,\\ 6,6,7,10,12,12,12,12,12,10,8,7]$$

$$G_{k2} = [6,6,6,6,5,5,6,5,5,5,5,6,\\ 6,6,6,10,12,12,12,12,12,10,8,7]$$

$$G_{k3} = [6,6,6,6,6,6,7,5,6,6,5,\\ 5,6,6,7,12,12,12,11,11,10,9,7]$$

The sum of the maximum power supply values (KWH) of all power suppliers in each period is

$$G_k = [18,18,17,17,17,17,20,15,17,17,16,\\ 17,18,18,20,30,36,36,36,35,35,30,25,21]$$

C. The Result of Simulation

The electricity consumption and electricity charge in a day are shown in Fig 3 and Fig 4 respectively.

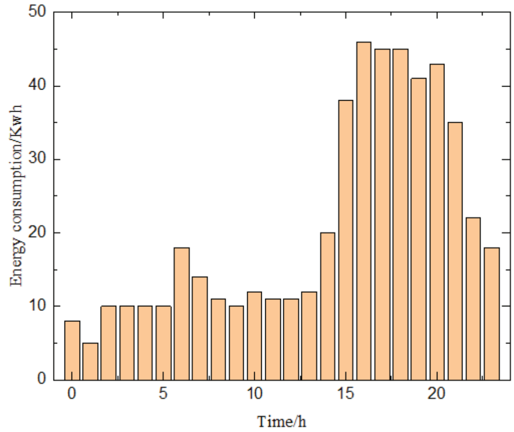

Fig 3 Energy consumption in one day before optimization

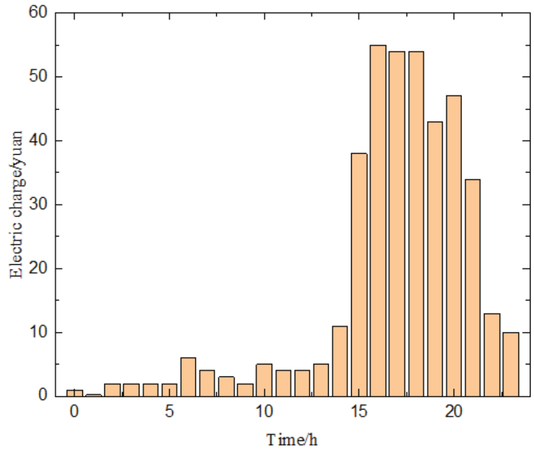

Fig 4 Electric charge in one day before optimization

From the Fig 3 and Fig 4, we can see that the total daily energy consumption of EV users was 506Kwh, and the total daily electricity consumption of EV users was 395.98 yuan before optimization. Between 15:00 and 21:00, electricity consumption peaks, and so do electricity bills.

When each EV user knows the real-time electricity price published by the power supplier and does not know the electricity consumption of other users, the local optimal decision is shown in Fig 5.

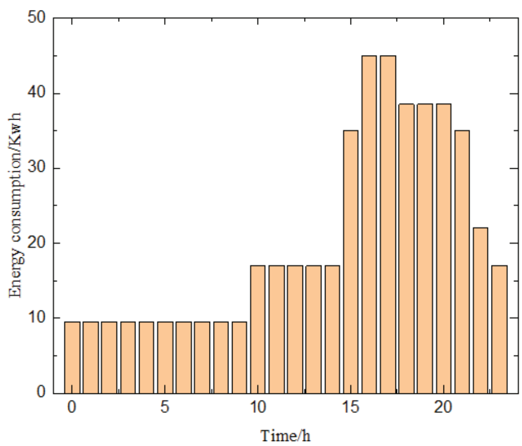

Fig 5 Energy consumption in one day after optimization

From Fig 5, we can see that the total daily energy consumption of EV users was 505Kwh after optimization, which is almost the same as before optimization. The optimization does not reduce electricity rates by forcing electric car users to use less electricity, so it's realistic.

The whole idea is to spread the amount of usage that exceeds the supplier's maximum supply value over other time periods. We give priority to time periods with lower electricity prices without distorting the energy consumption curve. That means it must be ensured that the peak hours of the day are still between 15:00 and 21:00, after sharing the excess electricity consumption. The energy consumption and electricity charge within one day after the second optimization are shown in Fig 6 and Fig 7 respectively.

From Fig 6 and Fig 7, the total daily energy consumption of all electric vehicle users is 505Kwh after the second optimization, which is almost the same as before optimization. The total daily electricity cost for all EV users was 332.2 yuan, 16.1 percent lower than 395.98 yuan before the optimization. Therefore, this optimization reduces the daily electricity bill of EV users without reducing the total amount of electricity consumed by EV users in a day, while still ensuring the peak electricity consumption from 15:00 to 21:00 a day.

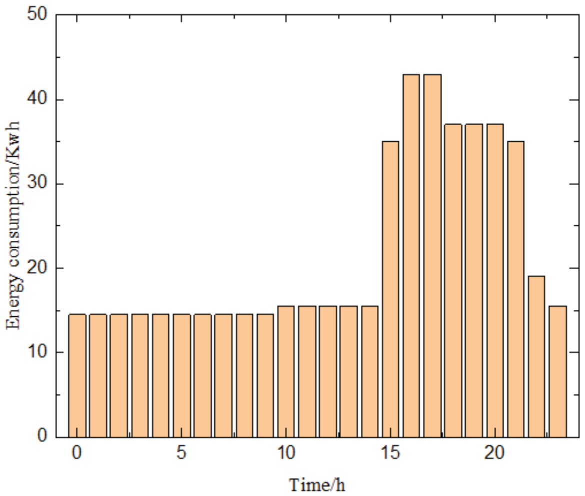

Fig 6 Energy consumption in one day after the second optimization

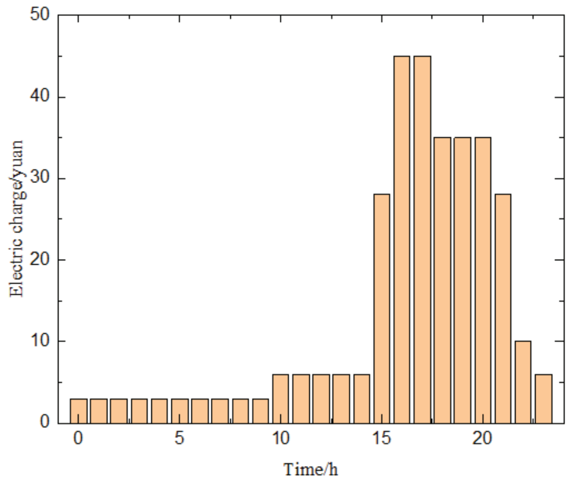

Fig 7 Electric charge in one day after the second optimization

However, this is the ideal scenario, in which all EV users are willing and actually able to use electricity at optimized values. In daily life, many users are not willing to change their original habit of using electricity according to the calculated optimal solution. We considered this case and compared the results with the optimized ones. The result of comparison is shown in Fig 8.

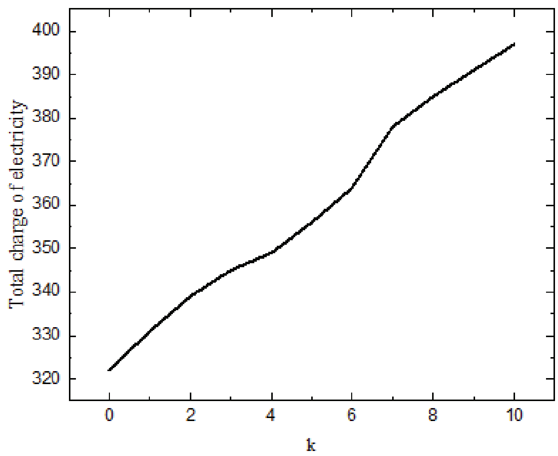

Fig 8 The change of total charge of electricity with the number of users who do not change their habit of using electricity k

We can see that the sum of all consumers' electricity bills increases as the number of consumers who do not change their consumption habits increases from Fig 8. This result also shows that the optimization effect of demand response management in this paper is very good. When some EV users don't purchase electricity according to the optimized result, the overall electricity bill will rise significantly.

V. Conclusion

This paper studies the distributed trading mechanism of electric vehicle energy in the smart grid. We analyzed the non-cooperative game between users and demonstrated that it costs EV users more to buy electricity from other users than from the central grid and that selling power to other customers is more profitable than selling power to the central grid. Next, we assumed that users can only purchase electricity from independent power suppliers and conducted demand response management. The conclusion is that the optimization result can reduce the electricity cost by 16.1%. Finally, we designed comparison experiments. The results show that the total electricity consumption of all electric vehicle users increases with the number of users who do not change their consumption habits.

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