Electric vehicle dispatching in smart charging station: a pricing strategy

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Abstract. With the rapid development of electric vehicles (EVs), intelligent charging stations will surely become the focus of development. However, the disordered charging of electric vehicles will cause unbalanced resource utilization. Therefore, it is necessary to study the scheduling problem of electric vehicles in charging stations. In this paper, we propose a new electric vehicle dispatching method to realize balanced utilization of resources and high economic benefits. We model the multi-charging station pricing strategy problem as a non-cooperative continuous strategy game with an integrated objective combining charging cost and charging station capacity. Then the existence of Nash equilibrium is proved, and we combining particle swarm optimization with iterative search method to solve the equilibrium point. Finally, a numerical example is given to demonstrate the effectiveness of the proposed method.

1. Introduction
As the world is facing the problems of environmental pollution [1] and energy crisis [2], the development of green economy is very important. On the one hand, the use of traditional fuel vehicles will produce a large number of harmful exhaust gases and pollute the environment; on the other hand, it intensifies the dependence on non-renewable petroleum resources. Compared with traditional vehicles, electric vehicles cannot only reduce pollutant emissions, but also have better controllability, stability and safety, so electric vehicles have great development value and market potential.

With the development of electric vehicles, it is inevitable to study the charging problem of electric vehicles. Electric vehicle charging has great randomness in time and space, which will have a great impact on the operation management and control scheduling of smart grids. From the perspective of smart grid applications, literature [3-5] respectively proposes a new routing protocol for smart grid applications based on wireless sensor networks to improve the reliable, efficient and intelligent operation of the grid. They also propose a new distributed routing protocol based on channel perception in literature [6], which improves the detection reliability and reduces the noise and congested spectrum bands. Literature [7] proposes a multi-objective optimization method to minimize the energy costs and emissions of residential micro-grids. For the proposed optimization method, the augmented ε-constraints and fuzzy decision-maker techniques are used to solve the problem.

As the basic charging facility for electric vehicles, electric vehicle charging stations (EVCS) play an important role in the development of electric vehicles. Literature [8] studies the location of charging stations. The authors in [8] establish a location model to minimize the total social cost based on genetic algorithm, and construct an evaluation index system under five location influencing factors.
Literature [9-11] study from the perspective of the benefits of charging stations. The authors in [9] design an optimal dynamic resource allocation scheme for electric vehicle parking lots. This scheme optimizes the cost of the parking lot owners’ Time of Use Demand Response program, while ensuring the interests of EVs owners. The authors in [10] propose a new economic-based EVCS queuing model. And the charging scheduling strategy that maximizes the long-term profit of charging station owners while minimizing the average delay of electric vehicles is studied. Then they consider the uncertainty of price and number of cars in [11], and establish the required model based on the stochastic optimization method. A long-term sustained profit algorithm for charging station owners is proposed to maximize the long-term profit of charging station owners.

Different from literature [10-11], we consider the real-time benefits of charging station owners, and we take economic benefits and balanced utilization of resources as the integrated optimization goal. In addition, the above literature only consider a single decision maker, and don’t consider the competitive relationship among multiple players. We use game theory to study the competitive relationship among multiple charging stations. Besides, we combine iterative search and particle swarm optimization [12] to give a solution algorithm. According to the real-time pricing strategy of charging stations, the charging scheduling of electric vehicles is carried out, and the balanced utilization of charging resources is realized. The main contributions of this paper can be summarized as follows:

• A new charging scheduling criterion for electric vehicles based on charging cost is defined.
• In this paper, a smart charging station with strong network communication ability, calculation ability and decision-making ability is considered. The game model of real-time competitive pricing strategy for multiple charging stations is constructed, and the solution algorithm is given.

Notations: $Z$ denotes the set of integers and $N^+$ the positive integers. $R$, $R^+$ is the set of real numbers and positive real numbers respectively. $[ \cdot ]$ represents a downward rounding operation.

2. Preliminaries

Traditional charging stations rely too much on manpower, and their scheduling is slow and difficult. While the intelligent charging station considered in this paper has strong computing ability and networking communication ability. We study the pricing strategy of charging stations in a certain area to realize the rational utilization of resources.

2.1. Charging costs of electric vehicles.

The charging cost of an EV can be divided into time cost and expense cost. Time cost consists of three parts: travel time $t_o$ from the charging point to the charging station; waiting time $t_w$ at a charging station; charging time $t_c$ required for the charging process.

Suppose there are $S$ charging stations in an area, each charging station has $R_i \left( R_i \in N^+, i \in S \right)$ charging piles, and the charging power is $P_i \left( P_i \in R^+ \right)$. Besides, the existing charging vehicles in each charging station are $n'_i \left( n'_i \in Z \right)$, and each EV needs to supplement $E_d \left( E_d \in R^+ \right)$ electric energy. Then, the charging time at charging station $i$ is $t'_i = \frac{E_d}{P_i}$, and the waiting time is the product of the queuing vehicles of each charging pile and the charging time, i.e. $t'_w = \left[ \frac{n'_i}{R_i} \right] \frac{E_d}{P_i}$.

**Remark 2.1:** As this paper studies the allocation of electric vehicles in a certain area, the influence of distance travel time on the selection of charging stations can be ignored. Besides, it is assumed that the charging power of all charging piles in each charging station is equal, each car needs to be
supplemented with equal power. This assumption is only to simplify the analysis and does not affect the subsequent results.

Expense cost mainly includes parking fee \( w_i^r \), electricity fee \( w_d^i \) and service fee \( w_f^i \), and their unit prices for charging station \( i (i \in S) \) is \( p_i^r \), \( p_d^i \), \( p_f^i \), respectively. According to the time cost, the corresponding expenses costs for charging station \( i \) can be obtained as \( w_i^r = (t_w^i + t_f^i) \cdot p_i^r \), \( w_d^i = E_d \cdot p_d^i \), and \( w_f^i = t_f^i \cdot p_f^i \).

### 2.2. Main problem.

In order to describe the main problem, we define an EVs allocation criterion based on expense cost.

**Definition 2.1:** Just considering the impact of expense cost on EVs allocation, the number of electric vehicles assigned to a charging station is inversely proportional to the total charge cost required by electric vehicles in the charging station. Assuming that there are \( m (m \in N^+ \) cars to be charged, then the number of electric vehicles assigned by charging station \( i \) is \( m_i (i \in S, m_i \in R) \):

\[
m_i = \frac{1}{\sum_{i=1}^{S} 1/w_i} \cdot m
\]

where \( w_i = w_i^r + w_d^i + w_f^i \) denotes the total cost of electric vehicle to charging station \( i \).

For electric vehicles, the total cost needs to be considered when choosing a charging station. However, for charging stations, the real income for charging stations is only the service fee. Assuming that there is a competitive relationship among charging stations in the region, each charging station is rational and selfish. Therefore, each charging station aims to maximize its own interests, that is, to maximize the total service fee.

**Assumption 2.1:** Assumed that \( p_i^r \) and \( p_d^i \) of each charging station are set by the parking lot and the power supply company.

**Problem 2.1:** The optimization goal of each charging station is:

\[
\max_{p_f^i} W_f^i
\]

s.t. \( p_f^\text{min} \leq p_f^i \leq p_f^\text{max} \)

where \( W_f^i = w_f^i \cdot m_i \) represents the total revenue of charging station \( i \).

Obviously, if a charging station aims to maximize its total service charge \( W_f^i \), it needs to choose the unit price as large as possible. However, an increase in the unit price of service fee will lead to a decrease in the number of electric cars it receives. Furthermore, the number of electric vehicles allocated by each charging station is not only affected by the unit price of its own service fee, but also affected by other charging stations’ price. So the influence of other charging stations’ pricing strategies should be considered when they choose pricing strategies.

From the previous discussion, it can be seen that each smart charging station has a limited number of charging piles. In order to realize the rational utilization of resources, the restriction of charging station capacity should be considered in the decision-making process. Assuming that the ideal capacity of electric vehicles in each charging station is \( n_d^i \), now this problem can be described as follows.

**Problem 2.2:** The optimization problem under an integrated objective of self-interest and ideal capacity constraints is:

\[
\max_{p_f^i} \left( \alpha \cdot W_f^i - \beta \cdot (n_d^i - m_i)^2 \right)
\]

s.t. \( p_f^\text{min} \leq p_f^i \leq p_f^\text{max} \)
where \( \alpha, \beta \in R \) are regulatory factors, which are used to adjust the order of magnitude. \( n_i' = n_i - n_i^0 \) is the ideal residual capacity, and \( p_{f,i}^{\text{min}}, p_{f,i}^{\text{max}} \) are the upper and lower limits of \( p_{f,i} \).

The current problem is how to determine the optimal pricing strategy for each charging station in the interactive decision-making process of multiple players.

3. **Non-cooperative game of smart charging station**

According to the previous analysis, there is an interactive decision-making process among multiple charging stations, and the game theory method can well solve this problem. In this section, we will model the pricing decision problem as a multi-player non-cooperative game based on Problem 2.2. The details are discussed as follows.

Define a non-cooperative game which is composed of three tuples: \( G = \{I, A, P\} \).

1) **Player:** \( I = \{1, 2, ... S\} \) is the set of the players, that is, all charging stations.

2) **Action:** \( A_i = \left[ p_{f,i}^{\text{min}}, p_{f,i}^{\text{max}} \right] \) is a compact set denoting the actions available to player \( i \). At every decision moment, each charging station chooses the price \( p_{f,i} \in A_i \).

3) **Payoff:** \( P_i(A) = \alpha \cdot W_j - \beta \cdot (n_i' - m_i)^2 \) is the payoff of player \( i \) under all players’ actions \( A \).

**Assumption 3.1:** Game \( G \) is a static non-cooperative game with complete information, which means that every player knows the triplet \( G \), besides, all players are assumed to be rational and the rationality is common knowledge [13].

In this game, every player will choose the price in set \( A_i \) to maximize his payoff. After each charging station chooses a pricing strategy, no player can get more by changing his own strategy. Then we say that the current strategy set constitutes a Nash equilibrium [14].

**Theorem 3.1 [14]:** Let \( G = \{K, \{S_i\}_{i \in K}, \{U_i\}_{i \in K}\} \) be an static strategic non-cooperative game, where \( K \) is a finite set of players, \( S_i \) is the set of strategies of player \( i \) and \( U_i \) is payoff function. If \( \forall i \in K : S_i \) is a compact and convex set; \( U_i(s) \) is a continuous function of strategies \( s \) and quasi-concave in \( s_i \), then \( G \) has at least one pure NE.

Obviously, \( \left[ p_{f,i}^{\text{min}}, p_{f,i}^{\text{max}} \right] \) is a compact and convex set, the player’s payoff is a continuous function, so now we only need to prove that \( P_i \) is quasi-concave in \( p_{f,i} \). As each player has the same form of payoff, we only need to take player \( i \) as an example to verify, the proof of its quasi-concavity will be illustrated graphically in next section.

The solution of Nash equilibrium is a complicated problem, but now there are many algorithms, such as min-max optimization algorithm, linear programming algorithm, iterative search method. Among them, iterative search method is suitable for solving the continuous strategy equilibrium. In addition, particle swarm optimization algorithm has fast search speed, high efficiency, and simple algorithm. So we combine particle swarm optimization (PSO) and iterative search method to solve the equilibrium strategy. The specific solution process is summarized in Algorithm 1.

**Algorithm 1** Equilibrium strategy solution

1: Input the relevant parameters required to build the game model.
2: Establish a non-cooperative game model based on the previous analysis and Problem 2.2.
3: Initialize the equilibrium point of each player, which can be selected according to relevant experience. We randomly select the initial value in the strategy space.
4: Each charging station makes decision optimization in turn with other players’ actions fixed, i.e.
5: Judge whether the Nash equilibrium condition is true.
    If $\forall i \in S, p'_{i,0} = p'_{i,k}$, then output the current optimal strategy combination.
    else return to step 4.

6: The process iterates until the Nash equilibrium is found.

4. Results and discussion

The following is a numerical simulation of electric vehicle scheduling based on charging station pricing strategy. Assumes that there are 40 electric cars in a certain area, each car needs to be supplemented with 20kwh electric energy. And there are four competitive charging stations, the service fee is limited to a range of 5-20 yuan/h, and $\alpha=0.1$, $\beta=5$. Other required data is shown in Table 1.

| Charging station | Charging pile | Ideal remaining capacity | Other expenses | Charging time |
|------------------|---------------|--------------------------|----------------|--------------|
| C1               | 5             | 8                        | 20             | 0.8          |
| C2               | 4             | 11                       | 18             | 1            |
| C3               | 6             | 12                       | 17             | 1.3          |
| C4               | 4             | 10                       | 21             | 0.67         |

In order to prove the existence of the pure strategy Nash equilibrium point, it is necessary to explain the relationship between the target revenue of the charging station $P_i$ and the pricing of the service fee $p'_{i,j}$. We can simply make other irrelevant variables constant, and obtain the functional relationship as shown in Figure 1.

![Figure 1](image1.png)

**Figure 1.** Relationship between $P_i$ and $p'_{i,j}$.

Figure 1 shows that when other parameters are given, $P_i$ is a continuous concave function of $p'_{i,j}$. Besides, we know that each charging station has the same mathematical model, and the action set is a compact and convex set. So according to Figure 1 and Theorem 3.1, it can be proved that the non-cooperative game between multiple charging stations has pure strategy Nash equilibrium.

According to Table 1, we first use the Algorithm 1 based on particle swarm optimization (PSO) for simulation. After 2.030 seconds and 17 iterations, the equilibrium pricing strategy and the number of cars allocated by each charging station can be obtained. The results are shown in Table 2, and the iterative process is shown in Figure 2. It should be noted that the equilibrium solution is related to the selection of the initial value. Then we use simulated annealing (SA) algorithm [15] to replace the
particle swarm algorithm in Algorithm 1 for comparison. After 7.903 seconds and 11 iterations we can get the equilibrium strategy set. The iterative process is shown in Figure 3.

Compare the number of cars allocated by each charging station in Table 2 with the ideal remaining capacity in Table 1, the maximum difference between the two is 0.7175 and the minimum difference is only 0.2706, it is obvious that the two are very close. That is, under the pricing strategy obtained by Algorithm 1, the balanced utilization of the resources of each charging station is realized.

**Table 2. Results of Algorithm 1**

| Charging station | Optimal price | Number of cars allocated by each charging station |
|------------------|---------------|---------------------------------------------------|
| C1               | 15.0000       | 8.2856                                            |
| C2               | 6.7114        | 10.7294                                           |
| C3               | 5.0000        | 11.2825                                           |
| C4               | 9.4431        | 9.7025                                            |

It can be seen from Figure 2 and Figure 3 that the charging station pricing under the two algorithms can quickly converge to the equilibrium pricing policy after a limited number of iterations. This proves the effectiveness of our scheduling strategy. But the simulation time of PSO algorithm is shorter, for example, when we increase the number of charging stations to 10 and the number of cars to be charged to 100, the price can still converge to the equilibrium solution at a fast speed. This is very important in large-scale scenes.

5. Conclusions
Aiming at the electric vehicle scheduling problem of smart charging stations in an area, this paper simplifies other unnecessary factors, proposes a new optimization problem. We first set up an optimization model with an integrated objective combining charging cost and charging station capacity. Then, the competitive relationship among multiple charging stations is modeled as a non-cooperative game. Next, we present an algorithm combining particle swarm optimization (PSO) with iterative search to solve the equilibrium point. Finally, numerical simulations are used to verify the effectiveness and efficiency of our proposed scheme. Future work includes studying the interactive decision-making between charging stations and users.
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