Electric Vehicle Charging Scheduling Strategy based on Genetic Algorithm

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Abstract: When multiple electric vehicles need to be charged, it will take more time and money for the electric vehicles to randomly enter the charging stations during the disorderly scheduling process. In the meantime, the utilization rate of charging piles is different, and the load of power grid is heavier. In this paper, a charging scheduling strategy is designed considering the requests of multiple electric vehicles, which schedule in a way of overall parallel. In this charging scheduling strategy, electric vehicles will cost less time and money, the utilization rate of charging piles is more equal, and the power grid has minimum load. According to the charging scheduling strategy, a vehicle charging scheduling model is established based on multi-objective optimization. Technique for order preference by similarity to ideal solution is used to eliminate the dimensions of multiple objectives, and the genetic algorithm is used to solve the model. The simulation results show that the charging scheduling strategy can select appropriate charging stations for electric vehicles and achieve the goal of multi-objective optimization.

1. Introduction

To reduce the dependence on fossil energy and respond to the call of protecting environmental, the development of new energy vehicles has been supported by many countries. In the promotion stage of new energy vehicles, there are still many problems in charging service compared with fuel vehicles. The charging scheduling problem of electric vehicles has attracted many scholars around the world.

To avoid the power grid being overload, Haoyang Li [1] used Monte Carlo method to simulate the influence of electric vehicles in different numbers on the load curve of the power grid. He put forward an optimization method to determine the parameters of two-stage peak-valley electricity price model by using genetic algorithm. Xiaowei Jiang [2] established a charging model and solved it by using genetic algorithm. This model can alleviate load fluctuations through orderly dispatching of real-time electricity prices, reduce the peak-valley difference of power grid and reduce charging cost.

To meet the requirements of users, power grid and charging stations, Tianpei Zhou [4] established a multiple objective optimization model, which consider the travelling-distance, deviation in...
utilization rate of charging piles. The charging scheduling model can effectively improve the utilization rate of charging stations, reduce the load of power grid and optimize the user experience. Pengcheng Wang [5] proposed an optimization model based on the assigned model. A comprehensive optimization strategy is realized by estimating driving time, waiting time and charging time.

2. Multi-objective optimization model of electric vehicle charging scheduling

2.1. Problem description
When there are multiple electric vehicles have charging requests, in the case of disordered scheduling, the owner of electric vehicles will spend more time and cost a lot of money. In the meantime, some charging stations may be crowded, and the others are empty, and the power grid may be overload. Therefore, an efficient charging scheduling strategy should be designed to optimize these problems. In this paper, a multi-objective charging scheduling model is designed. And four areas are considered, including charging time, cost of charging, deviation of charging piles utilization and average charging power.

To reduce redundancy, considered the relationships between electric vehicles and charging piles directly rather than charging stations. This model assumes that there are $M$ electric vehicles need to recharge, and $N$ charging piles can provide charging positions.

2.2. Objective function
The symbols and their meanings used in this paper are shown in Table 1:

| symbol | meaning |
|--------|---------|
| $M$    | number of electric vehicles |
| $N$    | number of charging piles    |
| $P$    | basic data matrix of charging piles |
| $C$    | charging time matrix         |
| $D$    | driving time matrix          |
| $H$    | charging cost matrix         |
| $W$    | waiting time matrix          |
| $S$    | scheduling matrix            |
| $k$    | chromosome $k$ in population |
| $v_i$  | speed of $EV_i$              |
| $EV_i$ | electric vehicle $i$         |
| $CP_j$ | charging pile $j$            |

Suppose there are $M$ electric vehicles that need to be charged. Set a set of electric vehicles to $EV = \{EV_1, EV_2, ..., EV_M\}$. There are $N$ charging piles around. Set a set of charging piles to $CP = \{CP_1, CP_2, ..., CP_N\}$.

2.2.1. Minimum charging time
During the charging process of electric vehicles, we need to consider the driving time $t_{drive}$, the charging time $t_{charge}$ and the waiting time $t_{wait}$ to minimize the total charging time. As shown in Equation (1):

$$
\min F_1 = \sum_{i=1}^{M} \sum_{j=1}^{N} S_{i,j} \cdot (t_{drive,i,j} + t_{charge,i,j} + t_{wait,i,j})
$$
In Equation (1): $F_1$ represents the optimized objective function value; $S_{i,j}$ indicates that $CP_j$ is selected by $EV_i$; $t_{drive,i,j}$ represents the driving time from $EV_i$ to $CP_j$; $d_{i,j}$ represents the distance from $EV_i$ to $CP_j$; $v_j$ represents the driving speed of $EV_i$. In this paper, $t_{drive,i,j}$ have been calculated based on the basic data. We can use the data in the driving time matrix $D$ directly.

In Equation (2): $t_{drive,i,j} = \frac{d_{i,j}}{v_j}$

$t_{charge,i,j} = \frac{SOC_{finish,j} - SOC_{present,j} + d_{i,j} \cdot r_j}{P_j}$

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2.2.2. Lowest costs

In the charging process of electric vehicles, we need to consider the parking fee and the charging fee to make sure the total cost is minimum. As shown in Equation (4):

$$\min F_2 = W_{cost} + C_{cost}$$

$$W_{cost} = \sum_{j=1}^{N} \sum_{i=1}^{M} S_{i,j} \cdot C_{i,j} \cdot P_{j,2} + \sum_{j=1}^{M} W_{j,2} \cdot P_{j,2}$$

$$C_{cost} = \sum_{j=1}^{N} \sum_{i=1}^{M} S_{i,j} \cdot H_{i,j}$$

In Equations (4), (5) and (6): $W_{cost}$ represents the total parking fee; $P_{j,2}$ represents the unit price of $CP_j$; $W_{j,2}$ represents the waiting time from $EV_i$ to $CP_j$; $C_{cost}$ represents the total charging fee; $H_{i,j}$ represents $EV_i$ go to charge at $CP_j$.

2.2.3. Deviation of charging piles utilization

In the case of disordered scheduling, many charging vehicles may stop at some charging stations, there are only a few charging vehicles stop at the others. In order to balance the utilization rate of charging piles, the deviation of charging piles utilization should be considered. As shown in Equation (7):

$$\min F_3 = \frac{1}{N} \sum_{j=1}^{N} \frac{s_j^r \cdot c_j}{(aver_k - 1)^2}$$

$$aver = \sum_{j=1}^{N} s_j^r \cdot c_j$$
In Equation (7): when \( s_j = 1 \), electric vehicles go to recharge at \( CP_j \); \( c_j \) represents the charging time of an electric vehicle in \( CP_j \); \( \text{aver} \) represents the average charging time of each charging pile.

2.2.4. The load of power grid is minimum
Many vehicles charging at the same time will increase the load of the power grid. To avoid this situation, the average charging power of the scheduling scheme should be minimum. As shown in Equation (9):

\[
\min F_4 = \frac{C_p}{C_{\text{time}}}
\]

\[
C_{\text{time}} = \sum_{j=1}^{N} s_j^t \cdot c_j
\]

\[
C_p = \sum_{j=1}^{N} s_j^t \cdot c_j \cdot P_{j,4}
\]

In Equations (9), (10) and (11): \( C_p \) represents the total power consumption; \( C_{\text{time}} \) represents the total charging time; \( P_{j,4} \) represents the charging power of \( CP_j \).

2.3. The solution of multi-objective optimization model
There are many ways to solve the multi-objective optimization model. This paper use TOPSIS to solve the model to eliminate the dimensions. In this way, the multi-objective problem is transformed into a single-objective problem. As shown in Equation (12):

\[
\min Y = \lambda_1 \cdot \left( \frac{F_1 - \min F_1}{\max F_1 - \min F_1} \right)^2 + \lambda_2 \cdot \left( \frac{F_2 - \min F_2}{\max F_2 - \min F_2} \right)^2 + \\
\lambda_3 \cdot \left( \frac{F_3 - \min F_3}{\max F_3 - \min F_3} \right)^2 + \lambda_4 \cdot \left( \frac{F_4 - \min F_4}{\max F_4 - \min F_4} \right)^2
\]

In Equation (12), the symbols are the value of charging time \( F_1 \), cost to recharge \( F_2 \), deviation of the charging piles utilization \( F_3 \), average charging power \( F_4 \) and the total fitness value \( Y \).

To solve Equation (12), we use genetic algorithm to simulate this problem via MATLAB.

3. Analysis of simulation results of the charging scheduling model
In the simulation experiment, suppose there are \( M \) electric cars that need to be charged. Set a set of charging vehicles to \( EV' \), \( EV' = [EV_1, EV_2, \ldots, EV_M] \). There are five charging piles around. Set a set of charging piles to \( CP' \), \( CP' = [CP_1, CP_2, \ldots, CP_5] \).

3.1. Basic data of electric vehicles and charging stations
The basic data of electric vehicles and charging piles are shown in Table 2 and Table 3:
Table 2 Basic data of $EV$

| $EV$ | SOC | $SOC_{present}$ | $d_{ij}$ | $r_i$ |
|------|------|------------------|----------|-------|
| EV₁  | 40   | 8                | 50       | 0.10  |
| EV₂  | 50   | 10               | 60       | 0.11  |
| EV₃  | 50   | 10               | 40       | 0.15  |
| EV₄  | 40   | 8                | 40       | 0.10  |
| EV₅  | 50   | 10               | 50       | 0.12  |
| EV₆  | 40   | 8                | 60       | 0.15  |
| EV₇  | 40   | 8                | 50       | 0.10  |
| EV₈  | 50   | 10               | 40       | 0.11  |

Table 3 Basic data of $CP$

| $CP$ | $SOC_{real}$ | parking cost | charging cost | rest charging cost | rest charging time |
|------|--------------|--------------|---------------|--------------------|-------------------|
| CP₁  | 20           | 7            | 1             | 0.4                |
| CP₂  | 60           | 8            | 0.7           | 1.2                |
| CP₃  | 25           | 9            | 0.4           | 0.5                |
| CP₄  | 60           | 8            | 0.7           | 1.2                |
| CP₅  | 30           | 7            | 0.4           | 0.5                |

3.2. Simulation process

In our simulation, eight electric vehicles need to be charged, and there are five charging piles around. The population iterates 200 times, whose size is 50. We set the crossover rate to 0.95, the mutation rate to 0.03, and the value of elitism is true.

The evolution of the total fitness with the number of generations is shown in Fig. 1.

![Figure 1 The evolution of the total fitness with the number of generations](image)

3.3. Result analysis

According to simulation results, we find the minimum value of charging time $F_1$, charging cost $F_2$, deviation of the utilization rate of charging piles $F_3$, average charging power $F_4$ and the total fitness value $Y$. In the meantime, we can find the other fitness values of $F_1$, $F_2$, $F_3$, $F_4$ and $Y$. Put these data in table 4.
Table 4 Data of optimal value

| Charging time | Charging cost | Total fitness | Deviation of charging piles utilization | Average charging power |
|---------------|---------------|---------------|----------------------------------------|------------------------|
| min \(F_1\)   | 12.668        | 254.4113      | 0.0372                                 | 0.07888                | 53.475                  |
| min \(F_2\)   | 15.1649       | 221.1327      | 0.0653                                 | 0.615                  | 54.58                   |
| min \(Y\)     | 14.233        | 241.433       | 0.0177                                 | 0.2602                 | 52.1546                 |
| min \(F_3\)   | 14.3421       | 263.1751      | 0.065                                 | 0.0345                 | 54.506                  |
| min \(F_4\)   | 16.257        | 288.317       | 0.0481                                 | 0.7128                 | 50                      |

It can be seen from Table 4 that the optimization results of the total fitness value are a compromise effect, comparing with the optimization results of charging time, cost to recharge, deviation of the charging piles utilization and average charging power. In the meantime, the total fitness value is minimum. Obviously, multi-objective optimization can reach the goals: reduce charging time; decrease cost; reduce the deviation of charging piles utilization; average the charging power. The results proved the validity of this charging scheduling model.

4. Conclusions

The development of electric vehicles is still in the promotion stage. Due to the limitation of battery technology, all brands of electric vehicles currently take a long time to recharge compared with gasoline vehicles. In the early stages, charging facilities are few and unevenly distributed. Without the guidance of charging scheduling strategy, the disorderly charging behavior of electric vehicles may bring a bad experience to the owners of electric vehicles. For example: the charging time is too long, and the charging cost is higher. At the same time, the disorderly charging behavior of electric vehicles may lead to unbalanced charging piles utilization and increase the load of power grid. The charging scheduling strategy of electric vehicles designed in this paper is solved by multi-objective optimization based on genetic algorithm. The simulation results demonstrate the feasibility of this scheduling model. It can guide the owner of electric vehicles to recharge in a standard and orderly way, which is more reasonable and can bring good experience.

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