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Study on site selection planning of urban electric vehicle charging station①

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Abstract

The large-scale development of electric vehicles (EVs) requires numerous charging stations to serve them, and the charging stations should be reasonably laid out and planned according to the charging demand of electric vehicles. Considering the costs of both operators and users, a site selection model for optimal layout planning of charging stations is constructed, and a queuing theory approach is used to determine the charging pile configuration to meet the charging demand in the planning area. To solve the difficulties of particle swarm global optimization search, the improved random drift particle swarm optimization (IRDPSO) and Voronoi diagram are used to jointly solve for the optimal layout of electric vehicles. The final arithmetic analysis verifies the feasibility and practicality of the model and algorithm, and the results show that the total social cost is minimized when the charging station is 9, the location of the charging station is close to the center of gravity and the layout is reasonable.

Key words: charging station, electric vehicle (EV), improved random drift particle swarm optimization (IRDPSO), optimal planning

0 Introduction

With China's environmental has put forward higher requirements for China's energy transformation, which will accelerate the process of replacing fuel vehicles with electric vehicles (EVs)[1]. With the joint promotion of policy and technological progress, electric vehicles have become a key development area for the automotive industry in various countries. Although the electric vehicle industry is developing rapidly, it is still in its early stage.

Numerous research institutions and researchers at home and abroad have researched the siting of charging facilities. Foreign research on the siting of EV charging facilities is mainly divided into two categories: classical siting models based on demand and comprehensive siting models based on actual measurement data. Ref. [2] established the siting model to minimize the distance between electric vehicles and charging stations. Ref. [3] developed an intelligent algorithm based on data-driven and particle swarm optimization (PSO) through a large number of global positioning system (GPS) trajectory data, taking the weekly trip data of taxis in Chengdu, China as an example, to determine the optimal location of the charging station by minimizing CO_2 emissions.

Domestic scholars mainly consider the site selection scheme from the characteristics of electric vehicles and mathematical models' construction. Ref. [4] analyzed the distribution forecast of electric vehicle charging demand and built a charging station location model intending to minimize the total cost of electric vehicle charging stations by using the double-layer dynamic queuing method and Voronoi diagram. Ref. [5] studied the location of charging and changing facilities for electric logistics vehicles, comprehensively considered the charging duration, charging mode, and other influencing factors, and established a charging and changing facility location model aimed at minimizing the sum of power cost, vehicle driving cost, opportunity cost and penalty cost under the charging and changing mode under the premise of no charging behavior under vehicle scheduling and path planning. Ref. [6] analyzed the factors that affect the location of the charging station, and combined with these factors, established a location model of the electric vehicle emergency charging station with the main method of the analytic hierarchy process (AHP), and then incorporated the goal programming method and the AHP into the model, and took a region as an example to conduct the location lay-

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out through the model method.

To accelerate the development of electric vehicles, selecting reasonable charging station locations and determining the optimal number of charging make-ups for each charging station are urgent problems to be solved. To address the above two problems, this paper proposes a multi-objective site-setting planning model based on the Voronoi diagram and improved random drift particle swarm optimization (IRDPSO) to obtain charging station locations, a model based on queueing theory to calculate the number of charging stakes, and a multi-objective site-setting planning model with charging station construction and operation cost, user's time-consuming cost and electricity price cost.

1 Electric vehicle siting and capacity planning model

The site selection planning of charging stations is a rather complex problem, which is restricted by many conditions. However, the two main factors that affect the site selection are the operators of charging stations and the users of electric vehicles. From the operators' perspective, it is mainly considered to meet the charging needs of EV users at the lowest cost, including construction costs, land construction costs, operation and maintenance costs, etc. For users, there are mainly two aspects. First, they will care about the distance and time to the charging station. If the time to the charging station is too long, the probability of users going to the charging station will be lower. Second, the user will also be concerned about whether the charging pile is idle when arriving at the charging station and the waiting time. The influencing factors of site selection are shown in Fig. 1.

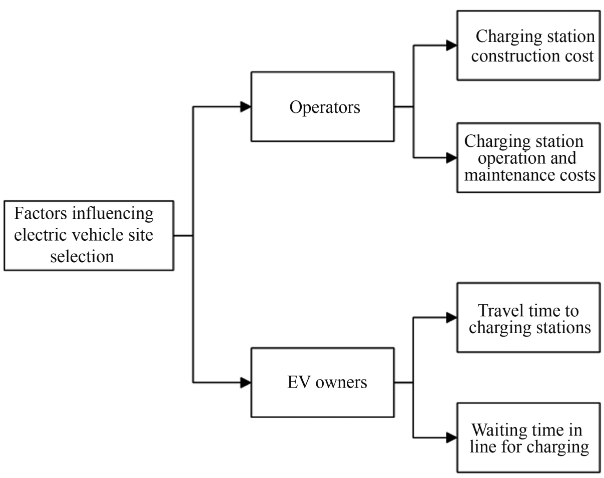

Fig. 1 Electric vehicle site selection influencing factors map

1.1 Objective function

The objective function mainly consists of two major parts, considering the costs of operators and users respectively. The operator includes the construction cost and operation cost of the charging station when building the station; for the user, it mainly includes two parts: the cost of time lost by the user to get to the charging station, and the cost of time spent in the charging queue.

(1) Operator's perspective

The construction cost of a charging station is mainly the total fixed investment cost consisting of charging pile cost, land cost, transformer cost, etc., while the number of charging piles determines the scale of the charging station, and the more the number of charging piles, the more the fixed investment required. Therefore, the fixed investment of the charging station can be expressed as a function of charging piles, which is expressed as

$$f(N_j) = W + \alpha N_j + \beta N_j^2 \tag{1}$$

where, W is the fixed investment cost of the charging station, including the cost of land and construction; N_j indicates the number of charging piles in the charging station; α indicates the unit price of the charging piles, and β indicates the investment coefficient related to the charging piles and auxiliary equipment.

Therefore, the annual construction cost of the charging station is

$$C_1 = \sum_{j=1}^{J} \left(f(N_j) \times \frac{r_0 (1 + r_0)^m}{(1 + r_0)^m - 1} \right) \tag{2}$$

where, r_0 denotes the discount rate, m denotes the depreciable life of the charging station, and J denotes the set of charging stations.

The operation and maintenance cost of the charging station can also be written as a function of the charging piles because the more the number of charging piles, the more the staff salary of the charging station, and the higher the maintenance cost of the equipment. Generally, it can be calculated by taking a certain percentage θ of the investment construction cost, so the annual operation and maintenance cost of the charging station can be expressed as

$$C_2 = \theta(W + \alpha N_j + \beta N_j^2) \tag{3}$$

(2) User perspective

The distance and time to the charging station will affect the charging decision behavior of the user. If the time to the charging station is too long, the probability of the user going to the charging station will be lower; On the contrary, it is higher. Then the time cost of EV users on the way of charging can be expressed as

$$C_3 = \frac{365\varphi}{v}\sum_{j=1}^{J}\sum_{i=1}^{I} p\, d_{ij}\, \lambda_{ij}\, n_i \tag{4}$$

where, φ denotes the time cost coefficient of charging per user trip, p is the probability of charging of EVs in a day, d_{ij} denotes the spatial linear distance from the demand point to the charging station, λ_{ij} denotes the non-linear coefficient of urban roads from the demand point to the charging station, and the square grid road is taken from 1.00 to 1.41[7], n_j is the number of EVs at the demand point, and v denotes the average driving speed of EVs in urban traffic.

When users arrive at a charging station, they are generally concerned about the availability of charging piles. When the number of electric vehicles is certain, the queuing time of vehicle owners waiting for charging decreases as the number of charging piles increases. Therefore, the user queuing time in the queuing theory is introduced, and the annual user queuing time cost is calculated as

$$C_4 = 365\varphi \sum_{j=1}^{J} T_q \sum_{i=1}^{I} p\, n_i \tag{5}$$

where, T_q denotes the average waiting time of EV owners at charging stations.

1.2 Constraints

(1) Constraints with the number of charging piles in each charging station.

$$\xi_j N_{j,\min} \leqslant N_j \leqslant \xi_j N_{j,\max} \tag{6}$$

where, ξ_j denotes the 0-1 state variable, $N_{j,\min}$ and $N_{j,\max}$ indicate the minimum and the maximum number of charging piles to be built in the charging station, respectively.

(2) Service scope constraints of charging stations.

$$\lambda_{ij} d_{ij} \leqslant d_{\max} \tag{7}$$

where λ_{ij} and d_{ij} are the same as the parameters of Eq. (4); $d_{\max}$ indicates the maximum distance from the charging demand point to the charging station.

(3) Inequality constraint on the distance between charging stations.

$$\lambda_{ij} D_{ij} \geqslant D_{\min} \tag{8}$$

2 Electric vehicle charging station planning

2.1 Electric vehicle charging demand

Charging demand is not only the premise to determine the number of charging stations, but also one of the important factors affecting the location and layout planning of charging stations.

Assuming that there are n road sections in the planning area and they are connected with the intersection node with the number of i. Use $p_t^x(j,j'_x)$ to represent the traffic flow density at junction j at time t, then the traffic flow density formula at junction j at time t can be expressed as

$$p_t^j = \sum_{x=1}^{n} p_t^x(j,j'_x) \tag{9}$$

If there are intersection Z nodes in this planning area, the total charging demand Q in the planning area in time T can be expressed as

$$Q = \sum_{j=1}^{Z}\int_0^T p_t^j \alpha\beta C_v \,\mathrm{d}t \tag{10}$$

where, α denotes the share of electric vehicle ownership in the planning area, β is the proportion of electric vehicles requiring charging in the area, and C_v is the average battery capacity of electric vehicles in the area.

2.2 Calculation of the number of charging stations

The number of charging stations is determined by the charging demand and capacity of charging stations, and since the capacity of charging stations is not uniformly determined, the number of charging stations is often difficult to calculate directly. Therefore, this subsection uses Eq. (10) to calculate the total charging demand of the planning area and then estimates the range of the number of charging stations with the maximum capacity limit of charging stations and the minimum capacity limit, then the formula for calculating the range of the number of charging stations in the planning area can be expressed as

$$\begin{cases} K_{\min} = \dfrac{Q}{S_{\max}} + 1 \\ K_{\max} = \dfrac{Q}{S_{\min}} \end{cases} \tag{11}$$

where, $K_{\min}$ denotes the lower limit of the number of charging stations in the planning area, $K_{\max}$ denotes the upper limit of the number of charging stations in the planning area, $S_{\max}$ is the maximum capacity limit of charging stations, $S_{\min}$ is the minimum capacity limit of charging stations, and Q is the total charging demand of electric vehicles in the planning area.

2.3 Charging pile configuration method based on queuing theory

The queuing theory model system is composed of three main parts: input process, queuing rules, and service organization, as shown in Fig. 2 for the structure of the queuing service system.

Under the influence of uncertainties such as the diversity of electric vehicles and operating conditions,

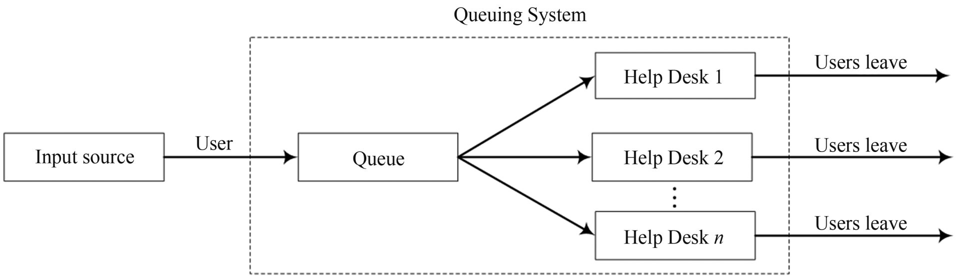

Fig. 2 Queuing service system structure diagram

it is assumed that the number of electric vehicles arriving at charging stations by users obeys a Poisson distribution with parameter λ and the time of electric vehicles enjoying charging service obeys a negative exponential distribution with parameter μ. Then the equilibrium equation of the electric vehicle charging facility service system is

$$\begin{cases} \lambda p_0 = \mu p_1 \\ \lambda p_{n-1} + (n+1)\mu p_{n+1} = (\lambda + n\mu)p_n \\ \lambda p_{n-1} + N\mu p_{n+1} = (\lambda + N\mu)p_n \end{cases} \quad (12)$$

where, N denotes the number of charging piles available for charging; n is the number of EVs in charging service; p_n denotes the probability that n electric vehicles are in charge.

The equilibrium equation of Eq. (12) is solved to obtain the probability of charging the electric vehicle as

$$\begin{cases} p_0 = \left[\sum_{k=0}^{N-1} \frac{1}{k!} \left(\frac{\lambda}{\mu}\right)^k + \frac{1}{N!} \frac{\mu}{\mu - \lambda} \left(\frac{\lambda}{\mu}\right)^N \right]^{-1} \\ p_n = \begin{cases} \frac{1}{n!}\left(\frac{\lambda}{\mu}\right)^n p_0 n \leqslant N \\ \frac{1}{N! N^{n-N}} \left(\frac{\lambda}{\mu}\right)^n p_0 n \geqslant N \end{cases} \end{cases} \quad (13)$$

From this, some operation indexes of electric vehicle charging can be solved as follows.

The service intensity of the charging pile is

$$\rho = \frac{\lambda}{\mu} \quad (14)$$

The utilization rate of charging piles is

$$\beta = \frac{\lambda}{N\mu} \quad (15)$$

The average queue length of the charging pile is

$$L_s = \frac{\rho^N \beta p_0}{N!(1-\beta)^2} + \frac{\lambda}{\mu} \quad (16)$$

The waiting time in line for electric vehicles is

$$T_q = \frac{L_q}{\lambda} \quad (17)$$

From Eq. (16), the average team length is obtained, such that the total cost expectation per unit of time is

$$M = C_s c + C_w L_s \quad (18)$$

where, c represents the number of charging piles, and L_s represents the average queue length of charging piles, C_s denotes the service cost per charging pile per unit time, and C_w is the cost per unit travel time of user queuing. Since the number of charging piles can only be an integer, the marginal analysis method is used to solve the model, and if the optimal number of charging piles is found, then:

$$M(c^* - 1) \leqslant M(c^*) \leqslant M(c^* + 1) \quad (19)$$

Substitute Eq. (18) into the above inequality to obtain:

$$M(c^*) - M(c^* + 1) \leqslant \frac{C_s}{C_w} \leqslant M(c^* - 1) - M(c^*) \quad (20)$$

2.4 Voronoi diagram and improved random drift particle swarm algorithm

The Voronoi diagram, also called the Tyson polygon diagram, was proposed and named after the Russian mathematician Voronoi[8] in 1908. It is composed of a group of continuous polygons composed of vertical bisectors connecting two adjacent point lines. In 1911, Dutch climatologist Thiessen[9] used the Voronoi diagram to divide the sensing range of weather stations to calculate the average rainfall, connected adjacent weather stations into a triangle, then made vertical bisectors for each side of the triangle, and connected the vertical bisectors into a polygon, i.e., Tyson polygon.

The particle swarm optimization is simple, easy to implement, and widely used in many applications, but the disadvantages of the algorithm are also obvious: as the particle population evolves and iterates, the diversity of its particles gradually decreases, which leads to the disadvantages of convergence too fast and falling into local optimality. IRDPSO, as a novel algorithm, has the advantages of fast convergence and high convergence accuracy, but it is rarely used in the solution of the charging station layout model at this stage.

In the random drift particle swarm optimization (RDPSO) algorithm, the search behavior of each particle is considered similar to the motion law of free electrons in a metallic conductor. Therefore, the search behavior of the particles in the RDPSO algorithm is considered a superposition of thermal and drift motions, i. e., the velocity of each particle is superimposed by both parts of the motion. Assuming that in the RDPSO algorithm, the velocity of the ith particle in the $t+1$ generation in the d-dimensional space is V_{id}^{t+1}, the velocity of the drifting motion is VD_{id}^{t+1}, and the velocity of the thermal motion is VR_{id}^{t+1}.

Then the velocity of the irregular thermal motion is

$$VR_{id}^{t+1} = \alpha \left| M_d^t - X_{id}^t \right| \varphi_{id}^t \tag{21}$$

where, α is the thermal coefficient, M_d^t denotes the average of the individual optimal positions of the particles, and φ_{id}^t denotes a random function obeying a normal distribution.

Then, using the learning mechanism that particles tend to local positions in PSO algorithm, the speed of drift movement is

$$VD_{id}^{t+1} = c_1 \cdot rand_1 \cdot (p_{id}^t - X_{id}^t) + c_2 \cdot rand_2 \cdot (p_{gd}^t - X_{id}^t) \tag{22}$$

where c_1 and c_2 are learning factors, $rand_1$ and $rand_2$ are random values in the range of $0-1$, p_{id}^t is the local optimal position of the particle, p_{gd}^t is the global optimal position of the particle, and X_{id}^t is the current particle position. The above equation can be equivalent to

$$VD_{id}^{t+1} = \beta (p_{id}^t - X_{id}^t) \tag{23}$$

where β indicates drift coefficient and is greater than 0.

The IRDPSO algorithm is a change in the velocity update equation based on RDPSO algorithm by replacing the average best position of the particles with the individual best position of each particle and adding crossover operations and greedy selection processes to achieve improvements as follows[10].

(1) Adding the crossover operation

This operation increases the diversity of the population and thus improves the performance of the algorithm by matching the particle update position with the local best position to create a new trial vector with the following expression.

$$X_{id(trial)}^{t+1} = \begin{cases} X_{id}^{t+1} 0 \leqslant rand \leqslant \eta \\ p_{id}^t \eta \leqslant rand \leqslant 1 \end{cases} \tag{24}$$

where $rand$ is a random number within $0-1$, η is the probability of performing the crossover operation, and after the crossover operation, a greedy selection process is used[11-12]. If the fitness value of the locally optimal position is low, a trial vector is used instead of the locally optimal position.

(2) Replace the average best position with the local best position

According to the extensive experiments on the RDPSO algorithm mentioned in Ref. [8], if the average optimal position in Eq. (21) is replaced by the local optimal position, the minimum total cost will be improved after a certain number of runs. Therefore, the speed update formula of the IRDPSO algorithm thermal motion is

$$VR_{id}^{t+1} = \alpha (p_{id}^t - X_{id}^t) \varphi_{id}^t \tag{25}$$

To sum up, the velocity and position update equations of IRDPSO are described as

$$V_{id}^{t+1} = \beta \cdot (p_{id}^t - X_{id}^t) + \alpha \cdot (p_{id}^t - X_{id}^t) \cdot \varphi_{id}^t \tag{26}$$

$$X_{id}^{t+1} = X_{id}^t + V_{id}^{t+1} \tag{27}$$

2.5 Joint Voronoi diagram and IRDPSO algorithm solving process

Although Voronoi diagrams are suitable for the characteristics of site selection, Voronoi diagrams lack the ability of global seeking. This paper uses the IRDPSO algorithm with the global stochastic seeking capability to solve jointly the Voronoi diagram. The specific planning steps are as follows.

Step 1 Import the charging demand at the demand point calculated according to Eq. (10).

Step 2 Initialize other parameters such as population size N, thermal coefficient α and drift coefficient β, the maximum number of iterations, and the number interval of charging piles in the charging station, and set the local optimum equal to the current population size.

Step 3 Calculate the range of the number of charging stations according to Eqs (9), (10) and (11) and initialize $N = N_{\min}$ to determine the initial locations of K charging stations by geometric methods.

Step 4 The velocities of the particles are randomly generated, and each particle includes K coordinates, representing the initial locations of K charging stations.

Step 5 For each particle, the Voronoi diagram is made with the charging station location as the growth element according to the station coordinates, to divide the service area of each charging station. The optimal number of charging piles in the charging station is calculated according to Eq. (20), and the process needs to satisfy the constraints of Eqs (6) to (8).

Step 6 Start the iteration, calculate the fitness value of the function, and update the local optimal position and the global optimal position of the particle.

Step 7 Update the velocity and position of the particle according to Eq. (26) and Eq. (27).

Step 8 Add crossover operations according to Eq. (24) and use a greedy selection process to update the local best position.

Step 9 Update the global best position.

Step 10 Determine whether the end condition is satisfied, if not, continue to loop back to Step 4 to continue execution.

Step 11 Stop the iteration and output the result.

The flow chart of model solving is shown in Fig. 3.

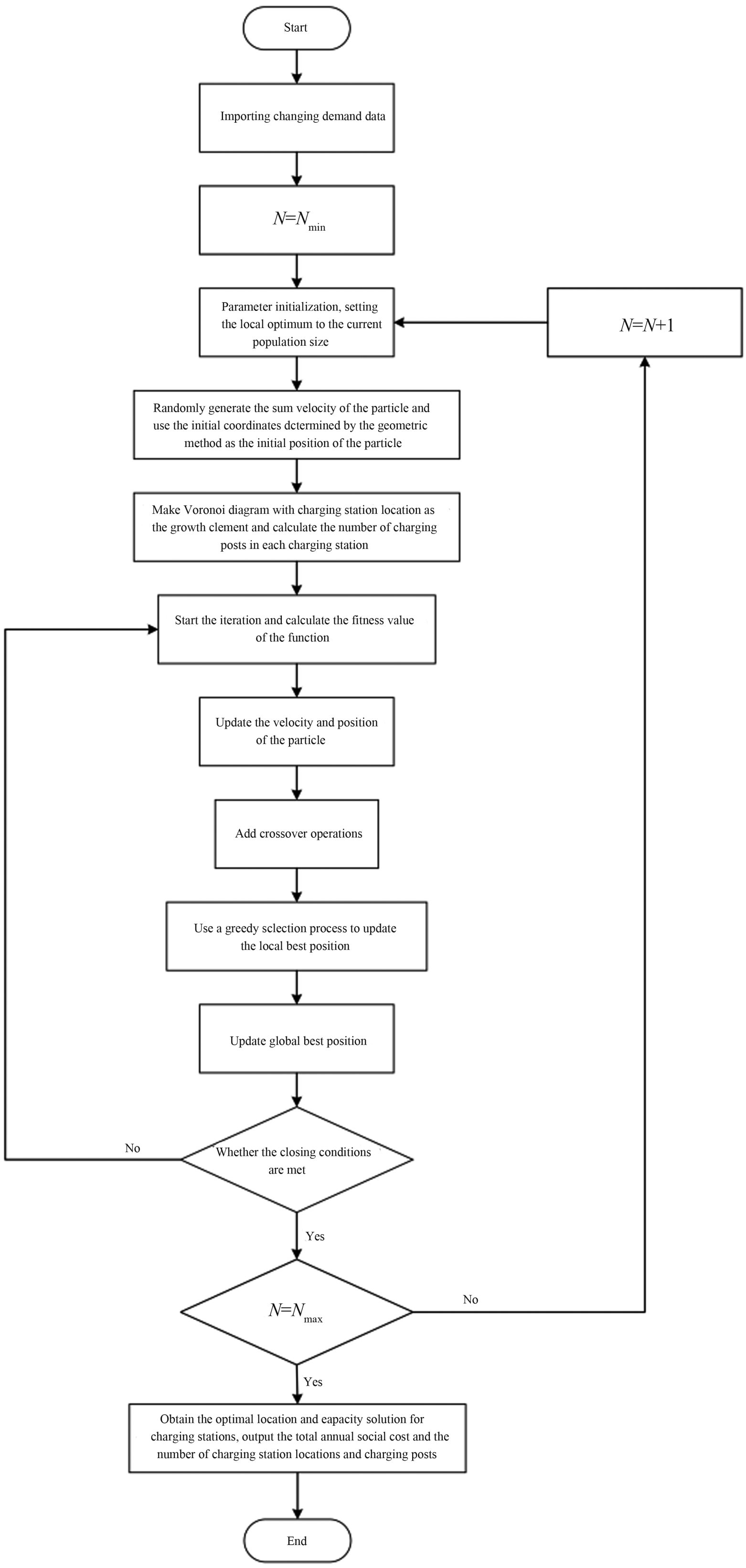

Fig. 3 Model solving flow chart

3 Calculation and analysis of algorithms

In order to verify the effectiveness of the model and algorithm, a planning area of 72 km^2, with 56 intersection nodes in total is taken as an example to carry out the planning and location of a charging station. The road network structure and traffic flow are shown in Fig. 4 and the number below the serial number indicates the number of electric vehicles.

The parameters in the calculation example refer to Ref. [13] and Ref. [14]; some parameters are shown in Table 1. The improved random drift particle swarm optimization algorithm is used to solve the location model to optimize the location of the charging station and calculate the total social cost of each planning scheme. The calculation results are shown in Table 2.

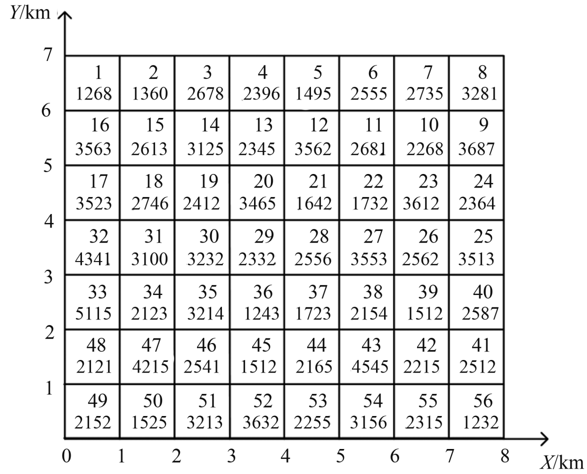

Fig. 4 Road network structure diagram

Table 1 Parameter setting

Parameter name	Symbol	Quantity	Unit
Fixed investment cost of charging station	W	100	10 000 yuan
Investment coefficient of charging pile	β	3	10 000 yuan/set^2
Scale factor	θ	0.1	\
Charging station discount rate	r_0	8%	\
Depreciation life of charging station	m	20	year
User unit travel cost	φ	50	yuan/h
Nonlinear coefficient of urban road	λ_{ij}	1.2	\
Charging probability	p	15%	\
Average driving speed	v	40	km/h
Minimum number of charging piles	$N_{j,\min}$	4	set
Maximum number of charging piles	$N_{j,\max}$	12	set

Table 2 Total social cost under different schemes

Number of charging stations	Annual construction and operation cost	Annual consumption cost of users during charging	Annual waiting time cost of users	Total annual social cost
6	1 476.540	1 362.125	8 059.000	10 897.665
7	1 659.165	1 356.297	7 805.764	10 821.226
8	1 853.211	1 353.816	7 375.750	10 582.777
9	2 048.572	1 342.483	6 967.429	10 358.484
10	2 234.136	1 339.317	6 917.768	10 491.221
11	2 431.376	1 334.661	6 948.066	10 714.103
12	2 626.037	1 330.241	6 762.815	10 719.093

It can be seen from the above table that when nine charging stations are built, the cost of the whole society is the lowest, which is 103.584 84 million yuan. The service scope of each charging station is shown in Fig. 5. The small box represents the charging demand point of the road network structure, and the small circle represents the location of the optimized charging station.

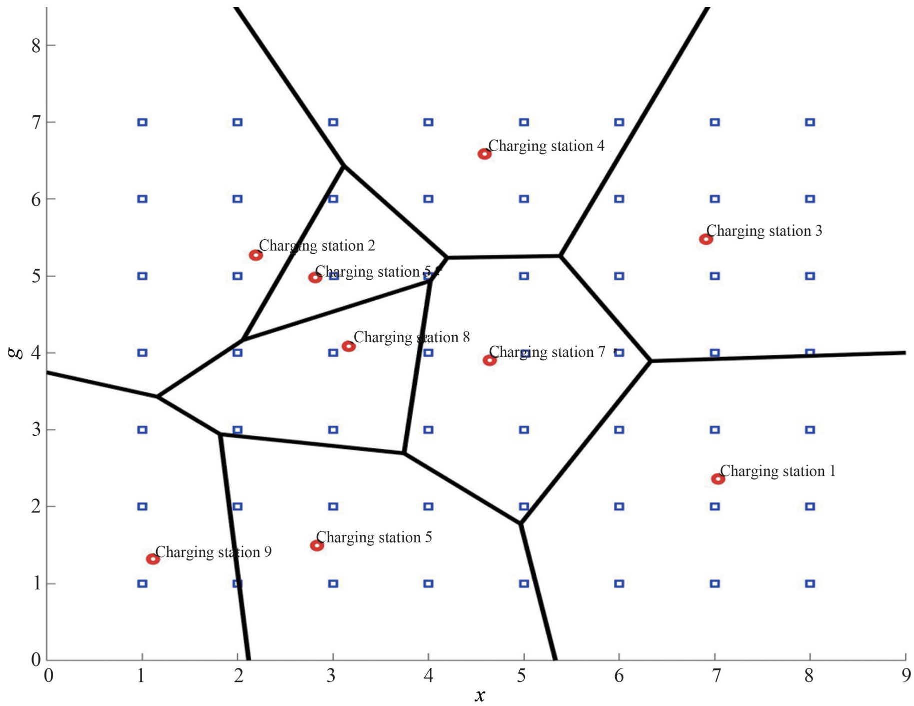

Fig. 5 Division of final service scope of charging station

It can be seen from the figure that the charging station site is evenly planned and close to the center of gravity[15], which indicates that the layout is reasonable and conducive to the development of electric vehicle charging facilities.

In this example, the traditional random drift particle swarm optimization algorithm and the improved random drift particle swarm optimization algorithm are used for simulation and comparison[16], and the comparison of fitness curve is shown in Fig. 6. It can be seen from the figure that the RDPSO has nearly the same iteration speed as the IRDPSO in 20 iterations, but after about 38 iterations, the RDPSO falls into the local optimal value, at which the fitness function value is 110.265 41 million yuan. Compared with RDPSO, the convergence speed of IRDPSO in the early stage has been greatly improved, and it converges smoothly in the middle stage and tends to be optimal gradually[17]. At this time, the fitness function value is 103.584 84 million yuan. The results show that the IRDPSO algorithm is better than the traditional RDPSO algorithm in terms of both the speed of convergence and the accuracy of convergence in the later stage[18]. The specific optimization results are shown in Table 3. The results show that the total comprehensive cost of the scheme obtained by IRDPSO is lower.

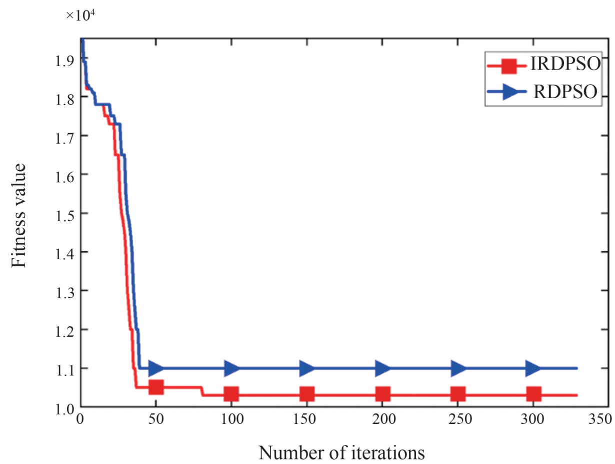

Fig. 6 Convergence curve comparison

Table 3 Comparison of PSO and IRDPSO algorithm optimization results

Algorithm	Annual construction and operation cost	Annual consumption cost of users during charging	Annual waiting time cost of users	Total annual social cost
RDPSO	2 221.698	1 362.125	7 442.718	11 026.541
IRDPSO	2 048.572	1 342.483	6 967.429	10 358.484

4 Conclusions

As a necessity of energy supply for electric vehicles, the construction planning and site selection of charging stations play a crucial role in the development of electric vehicles. Reasonable planning of the site selection of electric vehicle charging stations can not only reduce the cost of operators but also facilitate the travel of users, thus driving the development of the entire charging industry[19]. This paper constructs a charging station location model based on operators and users, designs an improved random drift particle swarm optimization algorithm to solve the model, and studies the location of electric vehicle charging stations in a planning area as an example. The specific conclusions are as follows.

(1) The charging station location model is constructed from the two aspects of charging station operators and electric vehicle users. The model is analyzed from the perspective of operators, taking into account the construction cost and operation cost of charging stations[20]. From the perspective of vehicle owners, the cost of users' annual charging journey time and the cost of users' annual waiting time for charging are considered.

(2) When solving the built charging station location model, the random drift particle swarm optimization algorithm is improved. By creating test vectors, the personal best position of each particle is replaced by the average best position of particles[21], and the cross operation and greedy selection process are added to achieve improvement.

(3) Taking a planning area as an example, the location model, IRDPSO algorithm, and Voronoi diagram are applied to the case. The solution results show that when there are 9 charging stations, the total social cost is the minimum, and the location of the charging station is close to the center of gravity, so the layout is reasonable.

This paper does not consider the type of electric vehicles, the impact on the power grid, and other factors, which need to be further studied in the future.

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