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Urban Electric Vehicle (EV) Charging Point Design Based on User Travel Big Data

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Abstract. A method was proposed to use big data to mine charging demand information of electric vehicles (EVs) and select location and construction scale of charging point. Firstly, the travel data of EV users were cleaned and analysed to obtain the available rules and corresponding digital characteristics. Secondly, according to Markov chain principle, the roulette wheel method was used to predict the spatial and temporal distribution of charging demand. Then particle swarm algorithm was used to optimize the selection of candidate sites. Finally, a typical region was taken as an example to prove the feasibility of this scheme.

1. Introduction

In the context of global energy shortage and serious environmental pollution, electric vehicles are gradually promoted due to their significant advantages of high efficiency and energy saving, zero emission and no pollution [1].Whether the charging facilities are perfect enough to meet users' charging needs is one of the important factors restricting the promotion of EVs. The problem of mismatch between supply and demand of charging facilities can be solved by reasonably planning the location and scale of charging points [2] [3].

At present, a large number of experts and scholars have carried out extensive research in the field of EV charging infrastructure planning. Firstly, charging demand was predicted according traffic network flow [4], electric vehicle keeping amount [5], or user charging behavior. Secondly, the siting and volumetric model was built. According to the objective function, the model can be divided into four main categories [6]: the impact on the power grid, the economic efficiency of charging facilities, the time distribution model aiming at the minimum queuing time of charging, and the spatial distribution model aiming at the weighted distance of facilities or traffic interception. Finally, the model was solved by the methods included Voronoi diagram and grid method, tabu search method, Floyd algorithm, genetic algorithm, particle swarm algorithm, etc. [7].

Most of the original sample data used in the existing literatures for charging demand prediction are the national household travel survey statistics published by the U.S. department of transportation [6] [8].The rhythm and habits are different between Chinese and American families, so the rules derived from the travel data of American families do not completely conform to China's national conditions. For this reason, Pan Mingyu, Liu Junyong and other scholars introduced relevant big data technology to carry out research in the field of EV charging facility planning [9-14]. Literature [9] analyzed the characteristics, sources and application difficulties of big data required in the process of planning and operating charging stations. Four big data integration modes suitable for charging stations were proposed. Literature [10-11] used big data technology to analyze and process the operation data of the electric vehicle industry, and revealed the characteristics of the electric vehicle industry. Literature [12] obtained the historical power redundancy and phase deviation degree of distribution transformer through data mining, based on which charging facilities are configured. Literature [13] obtained the elasticity coefficient representing the relationship between electricity price and demand by analyzing the big data of power load, and constructed the real-time electricity price optimization model of EV charging station to carry out orderly charging control, so as to realize peak load cutting and valley filling. Literature [14] analyzed the charging and discharging characteristics of electric vehicles by developing a multi-function big data service platform, and reduced the impact of uncertain charging on the distribution system through time-sharing electricity price. However, there are few existing researches on the specific applications and methods of big data in EV charging facility planning.

In recent years, the domestic big data platform has developed rapidly, which provides the possibility to use big data studying the travel rules of electric vehicles and carrying out charging facility planning. In this paper, EV charging demand information will be got through domestic EV travel big data mining, on the basis of which EV charging point location and capacity determination will be carried out.

2. The overall system

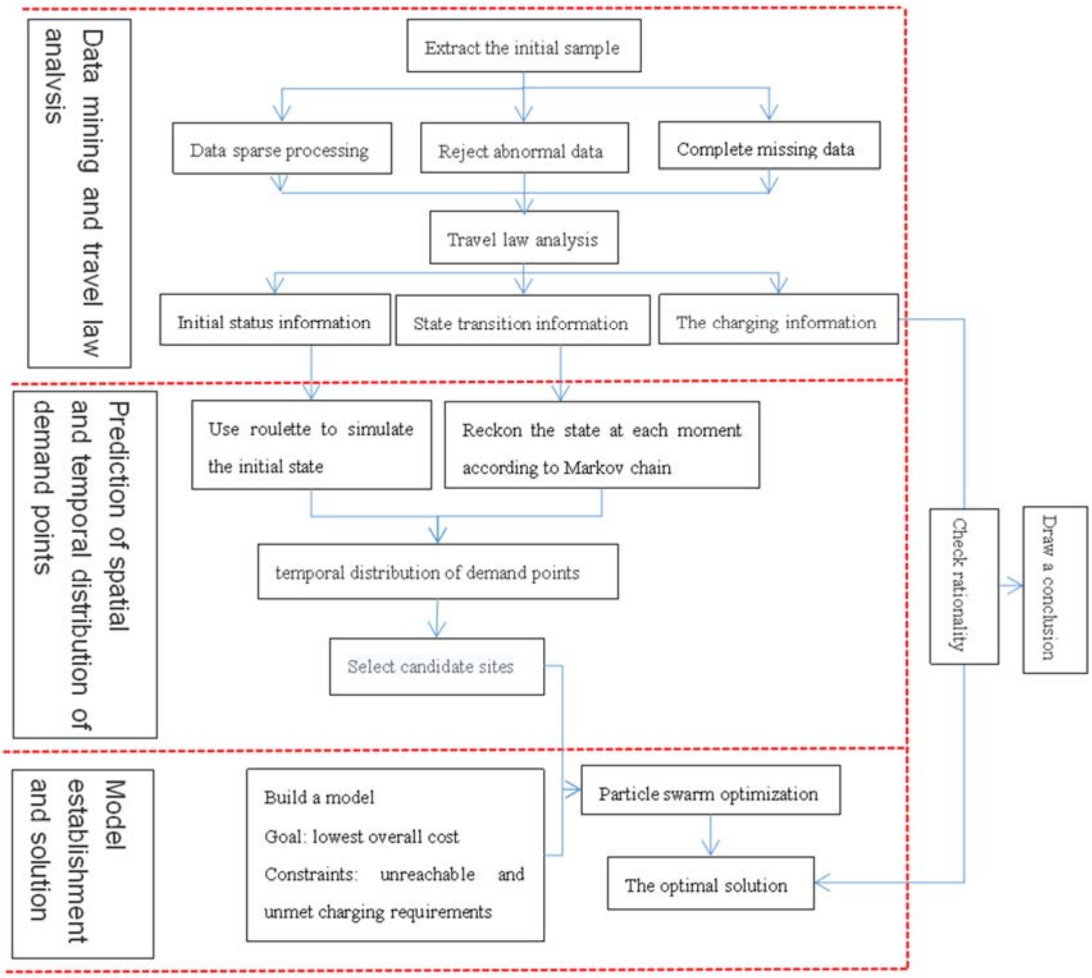

Figure 1. Framework system diagram.

The urban charging point planning method based on big data of EV travel mainly includes: data mining, travel rule analyzing and distribution of demand points forecasting by travel chain model, model establishment and solution. The main framework system and process are shown in figure 1.

The steps are explained as follows:

(1) Big data cleaning: Extract digital characteristics of EV travel laws in initial state, state transition and charging.

(2) Charging demand distribution prediction: Use the roulette method to simulate the starting time, place, power and daily mileage of a vehicle based on the law of starting state; Use Markov principle to forecast the travel status at each moment next based on the law of state transition, and accumulate the mileage until the daily mileage; Select charging demand points to present their spatial and temporal distribution.

(3) Select the candidate sites that meet the unreachable rate and the unsatisfied rate constraint, comprehensively considering of geographical factors and urban planning requirements.

(4) Find the optimal solution through establishing the model with lowest cost objective function and solving it by particle swarm algorithm.

(5) Compare the optimal solution in (4) with the charging information obtained in (1) to verify the scheme.

3. Big Data Mining and Analysis

3.1. Data Preprocessing

The initial sample data was obtained from the big data platform of Shanghai International Motor City. Nearly 200,000 electric vehicles in Shanghai are connected, and their information (including driving data, battery data, driving motor data, insulation resistance data, azimuth information and fuel consumption) were continuously uploaded at a frequency of 10-20 seconds in every 24 hours. The data mentioned above are large in scale, diverse in type, fast in change and low in value density.

Data cleaning and mining steps include:

(1) Extract charging and travel information of each EV: driving mileage, residual power (SOC), location information (GPS, namely longitude and latitude), vehicle status (driving, parking or charging), charging power (U*I) and their corresponding moment.

(2) Sparse data: Extract the data again at a frequency of 15 minutes.

(3) Abnormal data elimination and missing data completion: Eliminate inconsistent or mutational data of position or electric quantity information; Use interpolation method to complete the missing data.

(4) Sample availability judgment: The sample obtained through above processing is available if satisfied following conditions: the number of vehicles in the sample is not less than the 10% of actual possession number, and the time span of each vehicle information is not less than 6 hours. Otherwise repeat (1) to (3).

3.2. Digital Feature Extraction of Travel Rules

The travel rules of EV include charging information, starting state and state transition.

(1) Digital characteristics of starting state include: probability of travel time distribution, probability of daily starting electric quantity distribution, probability of daily starting position area distribution and probability of daily driving mileage distribution, as shown in figure 2.

It can be seen from the figure that the travel characteristics of electric private cars are different in weekdays and holidays, electric private cars and buses have different travel characteristics in the same date type, while the travel characteristics of electric buses are basically similar in weekdays and holidays.

The initial electric quantity distribution of private cars is close to the normal distribution, related to the randomness of private users' charging behaviors. Because of unified management, the buses are general required to ensure adequate power, at least 60% SOC, to start the travel.

Most of the private cars have daily mileage within 30 kilometers, and the long distance trips will be increased during holidays. Most of the buses have daily mileage within 90 kilometers, their long-distance trips are more than the private car, but the difference between working day and holiday is not obvious.

(2) Digital characteristics of state transition include: probability of state transition at each time of working days and holidays, as shown in figure 3.

It can be seen that the probabilities of transition from the same initial state to different states are different and change with time. The probabilities of transition from different initial states to the same state are different and vary with time. The transition probabilities of the same starting state have different trend in different date types.

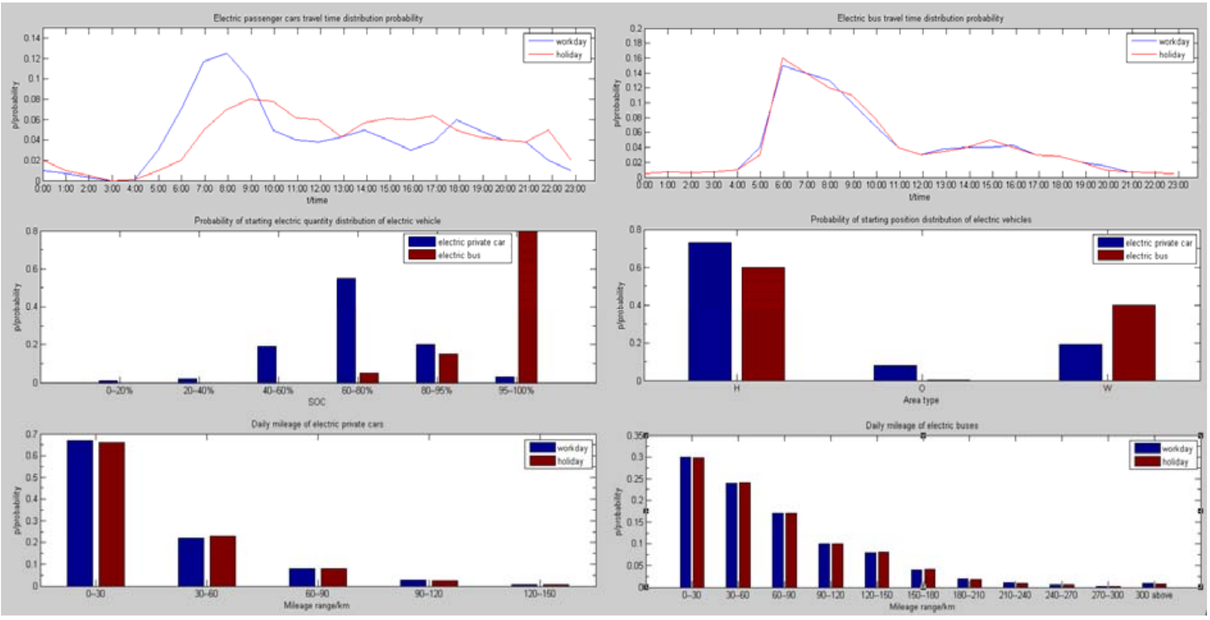

Figure 2. Probability of initial state.

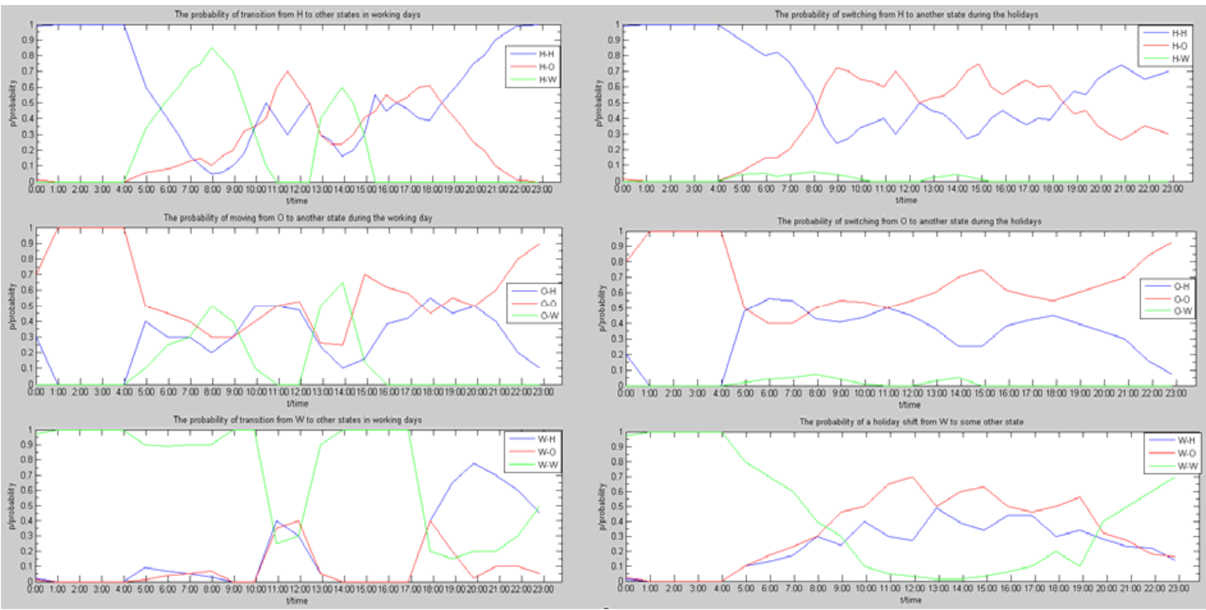

Figure 3. State transition probability.

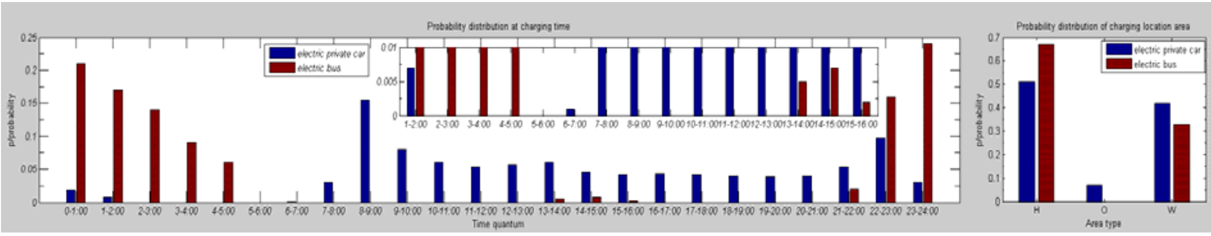

Figure 4. Charging information.

(3) Digital characteristics of charging include: probability of charging time distribution and probability of charging location area distribution, as shown in figure 4.

Electric buses operate mostly during the day, and their charging time is concentrated at night. The main role of private cars is to commute, they will be charged when users are at work or home, no matter day or night.

4. Charging demand prediction

4.1. Method Introduction

4.1.1. The roulette. Selection method used in this paper, namely the proportional selection operator, whose principle is: the probability of any individual being selected is proportional to its fitness function value.

The probability that x_i an individual with the fitness off *(xi)*, is selected in a population of size *N* is:

$$P(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{1}$$

In the process of travel state simulation, with probability as the fitness, the probability sum of all states of an EV at a certain moment is *1*, and any state appears randomly according to its probability.

$$P(x_i) = \frac{P(x_i)}{\sum_{j=1}^{N} f(x_j)} = \frac{P(x_i)}{1} = P(x_i) \tag{2}$$

In accordance with the principle of roulette.

Let the state probability of a vehicle at time t of a certain working day be *P (H) = 0.2, P (O) = 0.5, P (W) = 0.3*.Use roulette selection method to achieve simulation:

(1) Produce a random number *r* in [0, 1] according to uniform distribution;

(2) If r<=0.2, state at time t is *H*;

(3) If 0.2<r<=0.7, state at time t is *O*;

(4) If 0.7 < r < = 1, the state at time t is *W*.

4.1.2. Markov Chain. Markov property, also known as no memory or no aftereffect. For the discrete random variable x(t):

$$P\{x(t) = x|x(t_n) = x_n, \ldots, x(t_1) = x_1\} = P\{x(t) = x|x(t_n) = x_n\} \tag{3}$$

The change of position and state of electric vehicle conforms to Markov chain law.

Not all electric cars in the research area are connected to the platform, and this part of data needs to be supplemented by simulation. This paper mainly simulates the daily travel of electric private cars and electric buses in urban areas without considering special factors such as road repair and traffic jam.

4.2. State Simulation

4.2.1. Initial state. According to the distribution probability already obtained in 3.2, the roulette method was used to simulate the starting time, starting power and daily driving distance of each car. After selecting the starting urban area type, randomly generate a point in the area and set it as the starting point.

4.2.2. State at each moment. There are three position states of electric cars: H (in residential area), O (in commercial area), and W (in work area). Each car can only be one of these three states at any time. E_K^t means that the vehicle is in the region of K (including H, O and W) at time t, P (E_K^t) refers to the probability that the vehicle is in the state of $E_K^{t,}$ and $P_{h\text{-}k}^t$ refers to the probability that the vehicle changes from the state H (including H, O and W) at time t to the state K at time (t+1).$\mathbf{M}^t$ is the state transition probability matrix at time t, and it can be known from the conclusion of 3.2 that $\mathbf{M}^t$ is a time-varying matrix

$$\boldsymbol{M}^t = \begin{bmatrix} P_{H-H}^t & P_{H-O}^t & P_{H-W}^t \\ P_{O-H}^t & P_{O-O}^t & P_{O-W}^t \\ P_{W-H}^t & P_{W-O}^t & P_{W-W}^t \end{bmatrix} \tag{4}$$

The probability of the state at the next time:

$$\begin{bmatrix} P(E_H^{t-1}) \\ P(E_O^{t-1}) \\ P(E_W^{t-1}) \end{bmatrix}^T M^t = \begin{bmatrix} P(E_H^t) \\ P(E_O^t) \\ P(E_W^t) \end{bmatrix}^T \tag{5}$$

Starting from the initial time and position obtained in 4.2.1, the state probability at the next moment is obtained through the recursive calculation in formula (5).And then get the state at the next moment by roulette, find out the corresponding urban area type, select one randomly from them and take one of its road nodes as the position P^t of EV at time t. Finally, Dijkstra method is used to search the shortest path from P^{t-1} to P^t on the road network, and calculate the remaining power Q^t. When the cumulative mileage reaches the simulated daily mileage in 4.2.1, the trip is terminated.

4.3. Candidate Station Screening

If the vehicle needs to be charged at a certain place and time, the collection of the time and its corresponding geographical location is called the demand point, expressed as [*t; (x ,y)*], where *it* is the time, *x* is the longitude, and *y* is the latitude.

Set a minimum charging threshold, such as 20%.When the remaining power of an EV is less than 20%, the time is screened out and its corresponding geographical location is recorded. In order to improve the computing speed, the selected set of demand points is rearranged according to the time, and the spatial distribution of demand points at each time is drawn.

Firstly, the site that meets the requirements of urban planning is selected at the dense demand points. Then, according to formula (12), the unreachable rate of charging demand is calculated, and according to formula (13), the unsatisfied rate of charging demand is calculated. Finally, the site satisfying the constraint of in equation (12) and (13) is selected as the candidate station.

5. Model establishment and solution

5.1. Mathematical Model

A mixed integer nonlinear model of charging point planning is established with the goal of minimizing the comprehensive cost.

(1) Objective Function

$$\min F_{cost} = \sum_i \left(C_i^V + C_i^r\right) \tag{6}$$

C_i^V is the average annual capital consumption for the construction of charging point i:

$$C_i^V = \frac{r_0(1+r_0)^m}{(1+r_0)^m - 1}\left[A_i^L(S_i)C_i^L + Z_i^C(S_i)C^C\right] \tag{7}$$

Where, i E is the number of candidate stations, and I is a collection of candidate stations; $A_i^L(S_i)$ is the total floor area of station i, and C_i^L is the land price. Construction scale of station i is S_i E $\{0, 1, 2, ..., N\}$ (0 means never built; 1 means 8 chargers with a capacity of 50-150*kw*; 2 means 15 charging machines with 150-250*kw* capacity; 3 means 30 charging machines with 250-500*kw* capacity; 4 means 45 charging machines with 500-750*kw* capacity); $Z_i^C(S_i)$ is the capacity of station i, and C^C is its unit capacity cost. The number of operating years is m; the rate of return on investment is r_0.

C_i^r is the average annual cost of operating charging station i:

$$C_i^r = \sum_h \sum_{t=1}^{24}\left(p_g^t - p_c^t\right)d^h V_i^{th} + C_i^{HR} + C_i^m \tag{8}$$

Where, h E $\{1, 2\}$, 1 represents working day, 2 represents holiday, d^h is the number of days of typical h, and the total number of days in different typical is 365; At time t, the charging station buys electricity from the grid at the price of p_g^t=0.9 *yuan* / (*kW•h*) and sells it at the price of p_c^t =1.6 yuan / (kW•h). Staff salary of station i is C_i^{HR}, maintenance cost is C_i^m.

The total amount of electricity that station i needs to provide for the vehicle to be charged at time t on a typical date h

$$V_i^{th} = \sum_{n \subset N_i^{th}}\left(W_E - Q_n + \frac{Y_{ni}}{R_E}W_E\right) \tag{9}$$

In the formula, R_E is the maximum mileage that an electric vehicle can run with full power; For charging demand point n, the remaining electric quantity of the vehicle at this moment is Q_n, the distance of shortest path Y_{ni} to station i is obtained by Dijkstra method (if station i is not constructed, $Y_{ni}=\infty$).

At time t, the collection of points which have charging demand and can reach station i

$$N_i^{th} = \left\{n \middle| \frac{Y_{ni}}{R_E}W_E \le Q_n, n \in X_i^{th}\right\} \tag{10}$$

At time t, the collection of points which have charging demand and shortest distance to station i

$$X_i^{th} = \left\{n \middle| Y_{ni} = \min_{j \ne i}\left(Y_{nj}\right), n \in G^{th}, j \in I\right\} \tag{11}$$

Where, G^{th} includes all charging demand points in the urban area at time h and time t.

(2) Constraints

Unreachable rate: the percentage of vehicles that have charging needs but fail to reach the nearest charging station

$$\frac{[X_i^{th}] - [N_i^{th}]}{[X_i^{th}]} \le \eta \tag{12}$$

Where, [•] is used to find the number of elements contained in the set.

Unsatisfied rate: the rate of vehicles that arrive at a station but do not get a charger.

$$\frac{\max\left(0,[N_i^{th}]-X_i(S_i)\right)}{[N_i^{th}]} \leq \gamma \tag{13}$$

Where, $X_i\,(S_i)$ is the number of charging machines in the station.

The total investment shall not be greater than the maximum budget C_{max}

$$\sum_i C_i^V \leq C_{\max} \tag{14}$$

5.2. Solution Method

Particle swarm optimization algorithm is derived from the research on predatory behavior of birds. It is assumed that birds are particles without mass and volume, and forage in N-dimension space (N is the number of candidate stations in this paper). The position of particle j in N-dimension space is expressed as vector $x_j = (x_1,x_2,...,x_N)$, (in this paper, the position is the possible charging point construction scheme, i.e. the construction status S_i of N stations), and the flight speed is expressed as the vector $v_j = (v_1,v_2,...,v_n)$.Each particle has a fitness value determined by the objective function, and its flight experience is the best position p_{best} found so far (in this paper, the lower the fitness, the better).The experience of fellow particles is by far the best location g_{best} (the best in p_{best}) found for all particles in the entire population. The particle adjusts its next direction and speed by comparing its own experience with that of its peers until it finds the optimal solution.

The implementation process is as follows:

(1) Initialize a group of particles (population size N), including random position and velocity;

(2) Calculate the fitness value according to the following formula

$$F(X) = F_{\text{cost}} + \max(0, \textstyle\sum_i C_i^V - C_{\max}) \tag{15}$$

(3) Compare the adaptive value of each particle with it of the positions it has passed through, and find the best position p_{best};

(4) Compare the adaptive value of each particle with it of the best position the entire population have passed through, and find the best position g_{best};

(5) Adjust particle velocity and position according to the formulas

$$v_j = v_j + 2\text{rand}(0,1) \times \left(p_{bestj} - x_j\right) + 2\text{rand}(0,1) \times \left(g_{bestj} - x_j\right) \tag{16}$$

$$x_j = x_j + v_j \tag{17}$$

(6) Return to (2) loop until the number of iterations is greater than the maximum.

6. Example analysis

Take an urban area of 370 square kilometres as an example, with a population of 570, 000 and 12,000 electric cars (set as a common model in the market for simplified calculation, speed v_{EV}= 40*km/h* and nominal capacity W_{EV}= 60*kW·h*).The city is divided into 10 districts with main roads as the boundary, including three commercial districts (*O1, O2, O3*), four residential districts (*H1, H2, H3, H4*) and three working districts (*W1, W2, W3*).As shown in the figures below (the horizontal and ordinate represents the longitude and latitude of which the integer part were hidden). Initial parameter Settings: r_0=0.12, m =20 years, η=0, γ= 0.02, C_{max} = 50 million yuan.

The distribution of demand points can be obtained through simulation, taking 12:00 of a certain working day as an example, as shown in figure 5. According to the constraint conditions, the candidate sites are screened out as shown in figure 6.

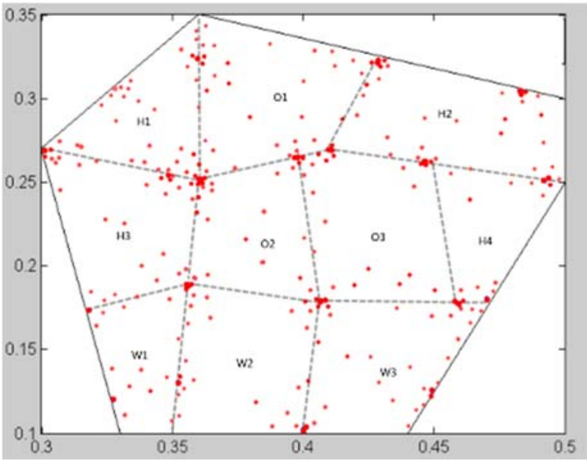

Figure 5. The distribution of demand points

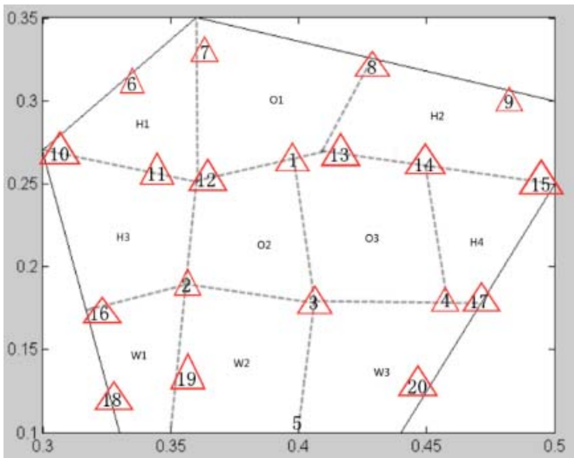

Figure 6. Numbers of candidate stations

Relevant parameters of charging station are shown in table 1 [15]. Construction costs include fixed costs except for land costs, such as equipment and construction. In the PSO process, there are 100 individuals in the initial population, and a maximum generations for 300. The optimal results are shown in table 2.

Table 1. Basic parameters of charging station

Charging station grade	Number of vehicles received/day	Construction costs/ million *yuan*	Number of chargers	Covers area/m^2
1	60	2.1	8	165
2	100	3.1	15	337
3	240	5.2	30	693
4	360	6.9	45	1085

Table 2. Optimization results

Charging point number	grade	Coordinates/ (Longitude, latitude)	Charging point number	grade	Coordinates/ (Longitude, latitude)
1	3	(0.4, 0.27)	11	4	(0.35, 0.26)
2	4	(0.36, 0.18)	12	0	
3	3	(0.41, 0.17)	13	0	
4	4	(0.46, 0.17)	14	4	(0.45, 0.27)
5	4	(0.4, 0.1)	15	2	(0.5, 0.25)
6	2	(0.34, 0.31)	16	2	(0.32, 0.175)
7	4	(0.36, 0.33	17	0	
8	3	(0.43, 0.325)	18	1	(0.325, 0.12)
9	3	(0.48, 0.31)	19	2	(0.355,0.14)
10	3	(0.31, 0.27)	20	3	(0.45, 0.125)

The final result was 17 out of 20 candidate stations, with a total cost of 15.49 million *yuan*. The selected sites are mostly distributed in residential buildings and work areas, but few in commercial areas, which conforms to the distribution law of EV charging areas in 3.2. The total cost is negative, indicating that the plan can be profitable and in line with the actual situation.

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