Deployment Optimization Strategies for Electric Vehicle Charging Stations

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Abstract. In recent years, with the gradual depletion of fossil energy and increasing environmental pollution, electric vehicles (EVs) have developed rapidly as one of the main substitutes for traditional fuel vehicles. Based on this, this paper firstly establishes a comprehensive optimization objective function including geographic information, charging time and charging amount. On the basis of determining the objective function, a quantum particle swarm optimization algorithm is proposed to solve the problem of optimal charging pile location and its number distribution. Secondly, a prediction model for the spatiotemporal distribution of electric vehicle users' charging demands based on fuzzy inference algorithm was proposed, and the charging load distribution curves of different functional areas were obtained by using Monte Carlo simulation method, which solved the spatiotemporal distribution of users' charging demands. Then, from the perspective of users, and taking into account the two-way cost of vehicle owners and charging station operators, a method of charging station location and capacity based on electric vehicle charging probability model is further proposed, which solves the problem of gradual expansion or reduction of charging piles. Finally, a multi-objective optimization model is established to solve the problem of optimal solutions for charging and battery swapping.

Keywords: Quantum Particle Swarm Optimization Algorithm, Fuzzy Inference Algorithm, Electric Vehicle Charging Probability Model, Multi-Objective Optimization.

1. Introduction

In recent years, with the gradual depletion of fossil energy and the increase of environmental pollution, electric vehicles have developed rapidly as the main substitute for traditional fuel vehicles. According to the International Energy Agency, the number of electric buses worldwide reached 7.2 million in 2019, an increase of 40% over 2018. Public electrical installations for charging cars have also grown rapidly, providing charging and maintenance for electric vehicles. However, problems such as lack of proper overall planning, low utilization rate, difficulty in finding piles, and long charging delay time will affect the progress of the project. The purpose of this competition is to ensure the optimal location and capacity of public charging stations in the city through mathematical simulations, thereby improving overall social benefits.

Since many relevant parties, including manufacturers and operators of charging stations (hereinafter referred to as "charging stations"), electric vehicle users and network users, have participated in the construction and operation of charging stations [1]. The interests of different stakeholders are not aligned. For example, if the investment in charging stations increases, users of electric vehicles can benefit from better charging services, but they may experience reduced income due to the high damage rate of charging units and the cost of operation and operation; by contrast, users of electric vehicles will not be able to obtain reliable charging services, such as insufficient or too far charging units, and long queues [2].

The placement of charging stations in electric vehicles mainly depends on the spatiotemporal distribution of charging demands of electric vehicle users. The spatiotemporal dispersion of electric locomotive loads is affected by factors such as size, motion characteristics and load characteristics. In general, high-traffic areas have higher demand for transportation, and high-traffic areas have less [3]. At the same time, the functional area of the city also affects the charging behavior of electric vehicles. For example, electric vehicle users are more likely to choose hotels, supermarkets, parking lots, and other places that require parking and charging. With the emergence of big data acquisition and processing technology, data-driven has been widely used as a method to study practical problems [4].

2. Quantum particle swarm optimization algorithm

2.1. Particle Swarm Optimization

Particle swarm optimization algorithm has been widely used to solve optimization problems. One of its major drawbacks is that it converges slowly and sometimes prematurely, which confines the group to local minima.

In this chapter, all particles have corresponding fitness values, which are ultimately defined by functions. The velocity of the particle controls the movement of the particle, which in turn returns to the original space by moving. The algorithm uses random particles to initialize the population, and finally obtains the optimal solution. In the research space of dimensionality, the estimation of the velocity and position of the particle is realized in advance, and the best position it finds is tracked, which itself is the globally optimal position.

The specific steps are:

(1) Particle optimization with time-varying inertial weights:

$$\omega^t = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} t \tag{1}$$

Where $t_{\max}$ is the maximum number of iterations, t is the current iteration, $\omega_{\max}$ and $\omega_{\min}$ is the initial and final value of the inertia weight.

(2) Particle swarm optimization algorithm with time-varying acceleration coefficient

This development was achieved by modifying the speed-up efficiency c_1 and c_2:

$$c_1^t = c_1^{\max} - \left(c_1^{\max} - c_1^{\min}\right)\frac{t}{t_{maax}} \tag{2}$$

$$c_2^t = c_2^{\min} - \left(c_2^{\max} - c_2^{\min}\right)\frac{t}{t_{maax}} \tag{3}$$

Where, $c_1^{\max}$ is $c_2^{\min}$ the initial value, c_1 and c_2 is the final value, which is the maximum number of purges allowed.

(3) Unified particle

Every product produced is subject to national and global standards. In this way, the influence of cognitive terminology and social factors on the algorithm can be effectively balanced. Related speed updates:

$$v_{ij}^{t+1} = \omega^t v_{ij}^t + c_1 r_{1ij}\left(p_{ij}^t - x_{ij}^t\right) * R_3 \tag{4}$$

where the uniform coefficients R_3 can be assigned between [0, 1] or fixed values between [0, 1].

(4) Fitness distance

A particle swarm optimization algorithm based on particle swarm optimization algorithm is proposed. to learn social experiences from other particles, not just from the best locations discovered so far. Its speed becomes:

$$v_{ij}^{t+1} = \omega^t v_{ij}^t + c_1 r_{1ij}\left(p_{ij}^t - x_{ij}^t\right) + c_2 r_{2ij}\left(p_{ij}^t - x_{ij}^t\right) \quad (5)$$

c_3 is P_n the acceleration coefficient, r_{2ij} a random number uniformly distributed between [0, 1].

2.2. Genetic (PSO-GA) algorithm based on PSO operator

The algorithm steps are as follows:

(1) Initialize the population, design the population quantity and individual dimension according to the specific problem of optimization, each population has n individuals, and each individual is a d-dimensional vector. Initially calculate the individual fitness value to determine whether the optimal individual fitness value meets the preset requirements of the optimization problem.

(2) Perform the selection operation on all individuals of the population. This paper adopts the roulette method to select, and generates a new population with a relatively high fitness value through the selection operation.

(3) Perform the crossover operation on the newly generated n individuals. The crossover adopts the single-point crossover method, and the population update is completed through the crossover operation.

(4) Calculate the adaptation of the population Calculate the optimal gene PBEST of the individual population and the optimal gene GBEST of the population, and use PBEST and GBEST to mutate the population. The update method is the same as the update speed v of the particle mass and the update particle position x.

(5) Calculate the fitness of individuals who have performed all operations, find out the optimal fitness of the population, and judge whether the preset conditions are met, and the program terminates. Otherwise, repeat steps 2 to 5 until the program aborts, or the maximum number of iterations is reached.

The algorithm flow chart is shown in figure 1:

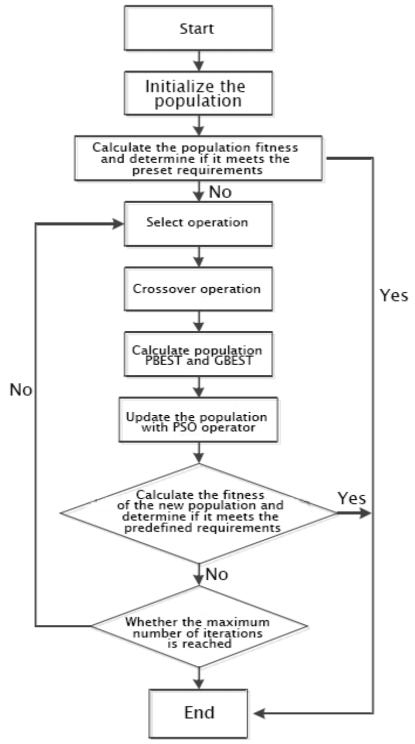

Figure 1. PSO-GA algorithm flow design diagram

2.3. Solution of the model

The parameters of the algorithm are selected as follows: the population size is 50; the variation range of the inertia factor is 0.4~0.8; the mutation probability is 0.04; the learning factor is both 2.0;

The hypothetical example is run independently for 50 times. It can be seen that under the given conditions, it is better to build 2,500 and 4,000 charging stations in the planning area, and it is optimal to build 3,323 charging stations in the planning area.

It can be seen from the calculation results that with the increase of the number of charging stations, the total cost will gradually increase, the calculation results are in line with the expected assumption, and the coordinates and grades of each charging station when building 3323 charging stations are shown in Table.1. It can be seen that the charging stations meet the charging demand constraints within their respective service ranges.

Table 1. Optimize calculation results

Numbering	grade	coordinate
1	4	(1243, 532)
2	3	(1521, 612)
3	2	(1634, 702)
4	1	(1845, 912)

Table.2 shows the comparison of the optimal calculation results using the QPSO algorithm and the PSO algorithm. Among them, the average result refers to the average of all convergent iteration results in 50 iterations; the average number of steps refers to the average of the iteration steps in 50 iterations. Figure 1 shows the comparison of the best fitness curves of the two algorithms. It can be seen from the figure that in the early stage of the iteration, the QPSO algorithm has a fast convergence speed and achieves the same calculation accuracy. The QPSO algorithm iterates more than 20 times less than the PSO algorithm; The optimal result found by the algorithm is better than that of the PSO algorithm.

Table 2. Algorithm performance comparison between QPSO and PSO

algorithm	Convergence times	average number of steps
Q PSO	32	52.3
PSO _	53	66.5

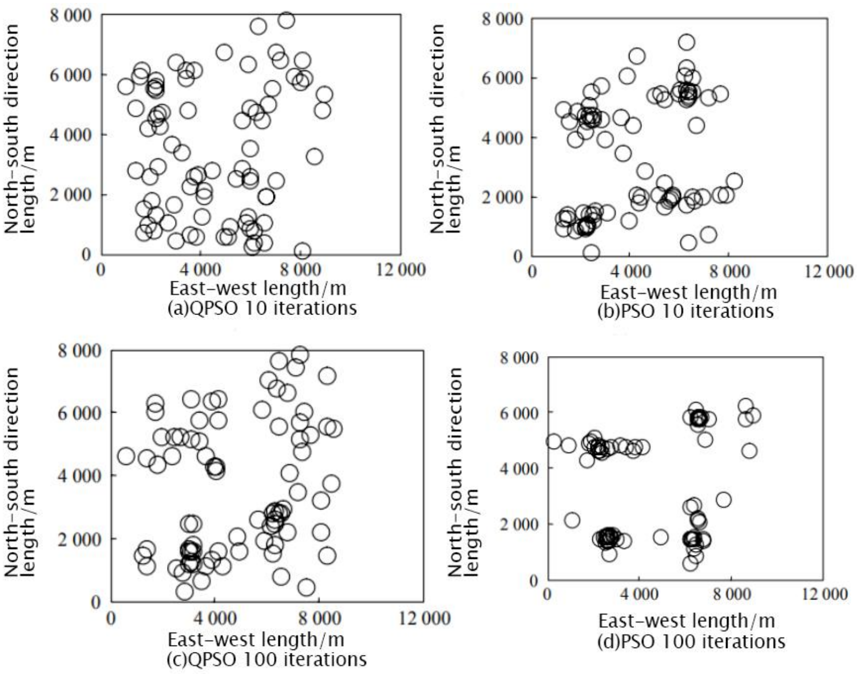

Figure 2. Particle Distribution Comparison Chart

The main reasons for the difference in performance between the two algorithms are: 1) QPSO algorithm adopts qubit probability amplitude encoding; 2) QPSO algorithm realizes particle mutation through quantum NOT gate. The second point is particularly obvious in Figure 2: the PSO algorithm has begun to appear particle aggregation after 10 iterations. On the one hand, it shows that the PSO algorithm has a faster convergence speed, and on the other hand, it also reflects that the PSO algorithm is prone to localization. The optimal one is insufficient; after 100 iterations, the population diversity of the PSO algorithm is seriously lost, while the QPSO algorithm still maintains a good population diversity. It can be seen that the QPSO algorithm using the qubit probability amplitude coding mechanism and mutation strategy is superior to the ordinary PSO algorithm in terms of search ability and optimization efficiency. Figure 3 shows the final site location obtained by the optimization calculation.

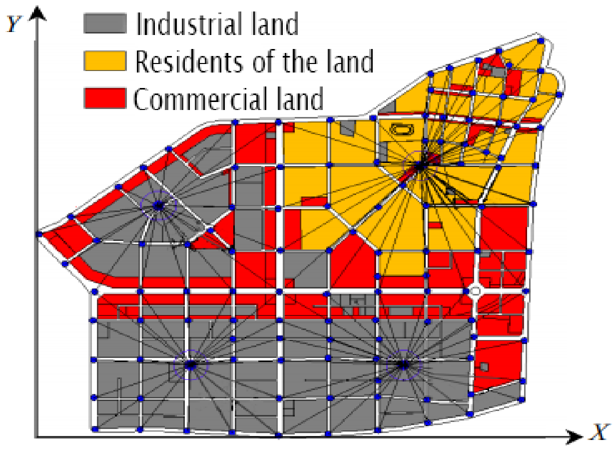

Figure 3. Optimal charging pile location

3. Fuzzy reasoning algorithm

3.1. Characteristic Quantitative Modeling of Travel Chains

Temporal feature quantity of the travel chain.

According to the data of NHTS 2009, the time when an electric vehicle leaves home for the first time basically conforms to a normal distribution, as shown in Equation 6,

$$Z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}, i = 1,2,\cdots,n;\ j = 1,2,\cdots,p \tag{6}$$

Figure 4 shows the probability density distribution of the first travel time.

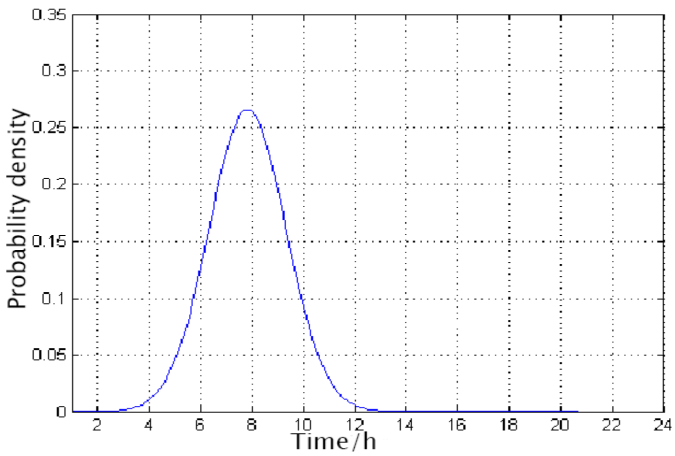

Figure 4. Probability density distribution of first travel time

For the parking time of the travel destination of the electric vehicle on the way, this paper uses the generalized extreme value distribution to describe, that is: the parking time of the work area and the commercial entertainment area obeys the generalized extreme value distribution function shown in Equation 7.

$$\sum_{i=1}^{c} u_{ik} = 1 u_{ik} \in (0,1) \tag{7}$$

Figure 5 shows the probability density distribution of parking time in the work area and the commercial and entertainment area.

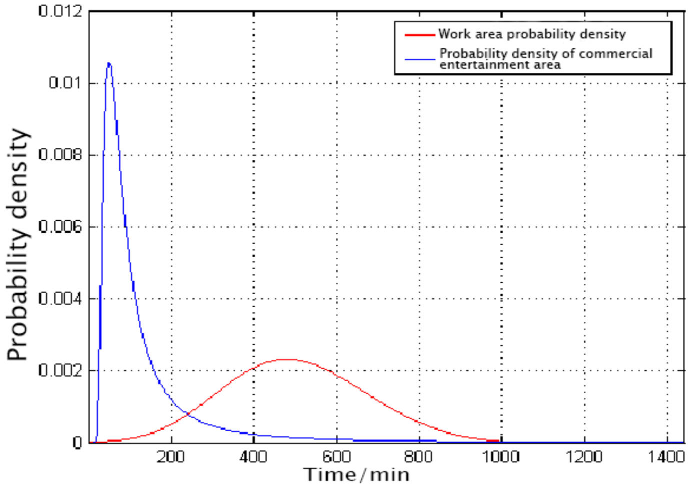

Figure 5. Probability Density Distribution of Parking Duration

3.2. Analysis of Electric Vehicle Charging Behavior Based on Fuzzy Reasoning Algorithm

The following formulas are used in the classification process, namely:

$$P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n) = \frac{P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n)\cdot P(c_1)}{P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n)\cdot P(c_1) + P(\omega_1,\omega_2,\cdots,\omega_n \mid c_2)\cdot P(c_2)}$$

Simplify the above formula:

$$\begin{aligned} P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n) &= \frac{P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n)\cdot P(c_1)}{P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n)\cdot P(c_1) + P(\omega_1,\omega_2,\cdots,\omega_n \mid c_2)\cdot P(c_2)} \\ &= \frac{1}{1+\dfrac{P(\omega_1,\omega_2,\cdots,\omega_n \mid c_2)\cdot P(c_2)}{P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n)\cdot P(c_1)}} \\ &= \frac{1}{1+\exp\left[\log\left(\dfrac{P(\omega_1,\omega_2,\cdots,\omega_n \mid c_2)\cdot P(c_2)}{P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n)\cdot P(c_1)}\right)\right]} \end{aligned}$$

Where the 1 in the denominator can be rewritten as:

$$1 = \frac{1}{1+\exp\left[\log\left(\dfrac{P(\omega_1,\omega_2,\cdots,\omega_n \mid c_2)\cdot P(c_2)}{P(c_1 \mid \omega_1,\omega_2,\cdots,\omega_n)\cdot P(c_1)}\right)\right]}$$

3.3. Solution of the model

The membership functions of charging probability, battery SOC, next trip mileage, and parking duration are shown in Figure 6 below.

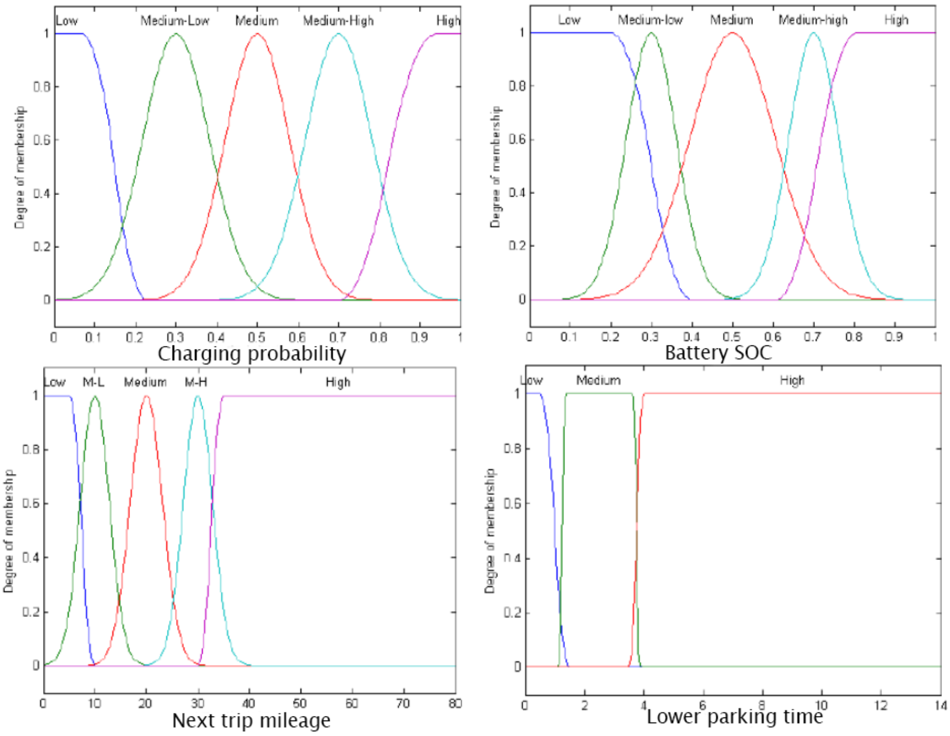

Figure 6. Spatiotemporal distribution

4. Electric vehicle charging probability model

4.1. Determination of the charging load to be planned and the number of charging stations

Definition 1: The charging station is i inserted into the charging pile index BoxOfficeIndex(i):

$$BoxOfficeIndex(i) = l;\ \ l = \{1, 2, 3, \cdots, 8\} \tag{8}$$

Formula (8), i is the grade after box office classification.
Definition 2: i the unplugged charging pile index ActorIndex(i) of the charging station:

$$ActorIndex(i) = \frac{1}{m}\sum_{j=1}^{m} b_j ; m = min\{4, m\} \tag{9}$$

Definition 3: i the arrival index of the charging station SequelIndex(i):

$$SequelIndex(i) = \begin{cases} 1, is\ a\ sequel \\ 0, not\ a\ sequel \end{cases} \tag{10}$$

CalendarIndex(i) of the charging station: i

$$CalendarIndex(i) = \begin{cases} 0, normal \\ 1, summer\ vacation \\ 2,\ festival \end{cases} \tag{11}$$

Definition 5: i duration index of charging station TypeIndex(i):

$$TypeIndex(i) = \begin{cases} 0, belong \\ 1, Does\ not\ belong \end{cases} \tag{12}$$

Definition 6: i the dwell time index of the charging station PraiseIndex(i):

$$PraiseIndex(i)=\frac{1}{k}\sum_{j=1}^{k}b_j \tag{13}$$

Definition 7: i ArrangeIndex(i) of the charging station's charge quantity index:

$$ArrangeIndex(i)=\frac{1}{k}\sum_{j=1}^{k}c_j;1\le c_j\le 100 \tag{14}$$

4.2. Division of Service Scope of Charging Stations

The division of the service range of the charging station is the premise of the location and capacity configuration of the charging station. In this paper, according to the Voronoi diagram, the service area can be automatically divided and the generation speed is fast, and it is used in the process of dividing the service range of the charging station [5]. Taking the initial location as the growth nucleus, expand outward at the same speed until they meet each other to form a graph on the plane. According to the generated Voronoi diagram, the original sub -regions are further re-divided. Figure 7 is a schematic diagram of the Voronoi diagram.

According to the charging habits of electric vehicle owners, this paper assumes that when electric vehicles have charging needs at intersection nodes, they will select the nearest charging station for charging, which is exactly in line with the characteristics of Voronoi diagram: the charging demand point in each sub-region is The distance of a region's growth nuclei is less than its distance to the growth nuclei of any other subregion.

$$Z_{ij}=\frac{x_{ij}-\overline{x}_j}{s_j},i=1,2,\cdots,n;j=1,2,\cdots,p \tag{15}$$

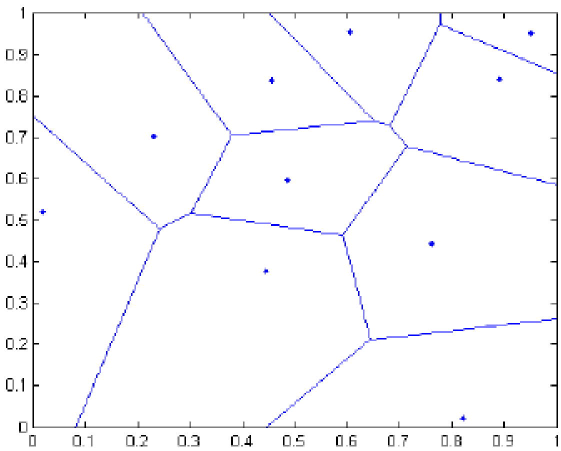

Figure 7. Voronoi diagram

4.3. Solution of the model

(1) Objective function

In the coverage objective function, U represents randomly generated demand points, and all demand fields are represented by us; where T is used for the identification of the center point of electric vehicle charging stations, and the center points of all electric vehicle charging stations are represented by TS; d_{TU} distance; T signal radius r_T; Afterwards, any base point T will be the set of points that satisfy the demands of all charging stations within the coverage radius $C_U(t)$, denoted by The distance between the center points of the car charging station,

$$C_U(t)=\{U\in US\mid d_{T,U}\le r_T\} \tag{16}$$

Charging area is designed to cover a minimum number of EV charging station central points to ensure full coverage of charging station demand points. Among them, US represents the overlap of demand point sets, and the minimum number of electric vehicle charging station center points is required in the electric vehicle charging station center point geometry T. Express:

$$US = \underset{t \in sdf}{U} C_U(T), s.t..Min|TS| \tag{17}$$

In the actual operation of the genetic algorithm, the coverage function of the center point of the electric vehicle charging station is represented by F-CT. When the center point of the electric vehicle charging station is given, the signal coverage factor of the center point of the electric vehicle charging station is calculated according to the center point of the electric vehicle charging station. Sigma TεTSCU(T) represents the total number of demand points covered by the center point of all EV charging stations, and the total number of charging station requests received in the experimental area. If the FCT covers 1, it means that when the coverage reaches 100%, it is better to cover the location model of the charging station. At this point, the location of the EV charging station center point is the best solution we are looking for. The optimal FCT objective function is expressed in Equation 18:

$$Maxf_{CT} = \frac{\sum_{t \in df} C_U(T)}{|US|} \tag{18}$$

(2) Quality objectives

In addition to covering all electric vehicle charging station center points, the construction of electric vehicle charging station center points must also consider the interference between adjacent bases. Due to the need for overlapping center points of multiple EV charging stations, charging stations in overlapping areas are protected from multiple signals that can affect charging quality. Especially when the base covers a large radius, the signal interference strength increases. Therefore, not only the cost and coverage area, but also the charging quality should be considered when choosing the construction site of the central point of the electric vehicle charging station. In the objective function, we use the ET variable to obtain the minimum signal strength from the center point of the T electric vehicle charging station at the charging station request point. ET is defined by Equation 19:

$$E_T = \frac{5}{(r_T + 1)^2} \tag{19}$$

Then, when the charging station requests the U point to receive the signal from the central point of the T electric vehicle charging station, the interference intensity is much larger than that of other adjacent electric vehicle charging station central points, educating the quality objectives determined during the construction of the main station into consideration , the F-SI function can be used, as shown in Equation 20:

$$Maxf_{ST} = \frac{\sum_{t \in df} \left(E_{T,U} / \left(E_{T,U} + \varphi(U) \right) \right)}{|US|} \tag{20}$$

(3) Final function objective

When calculating the genetic algorithm, the charging station location model not only considers the number of stations, but also considers the above-mentioned coverage objectives and quality. The importance of these two goals, as well as the weight of the goal coverage and quality goals.

The weight target range and quality target were determined using the expert consultation method. Through consultations and interviews with experts in various charging fields, it was found that the coverage target is 0.8 and the quality target is 1. The final function of the objective is the formula (21), where W1 is 0.8 and W2 is 1.

$$F = W_1 f_{CT} + W_2 f_{ST} \tag{21}$$

On the basis of the above analysis, the main objectives of the central point optimization planning for electric vehicle charging stations include cost objectives, coverage and quality. The purpose of the cost is primarily to determine the number of EV charging station center points based on the length of a problem. Therefore, in the optimization process of genetic algorithm, the function of coverage target and quality target is mainly studied, and finally through weighted optimization [6]. This function can be used as the fitness function in the process of genetic algorithm to estimate the individuality of adaptation, so as to select and extract individuals.

This paper takes the planning of electric vehicle charging station in Beijing Development Zone as an example, as shown in Figure 8. There are 48 intersection nodes and 110 road sections in the planning area. The specific traffic flow value setting of each intersection node can be found in Reference [7].

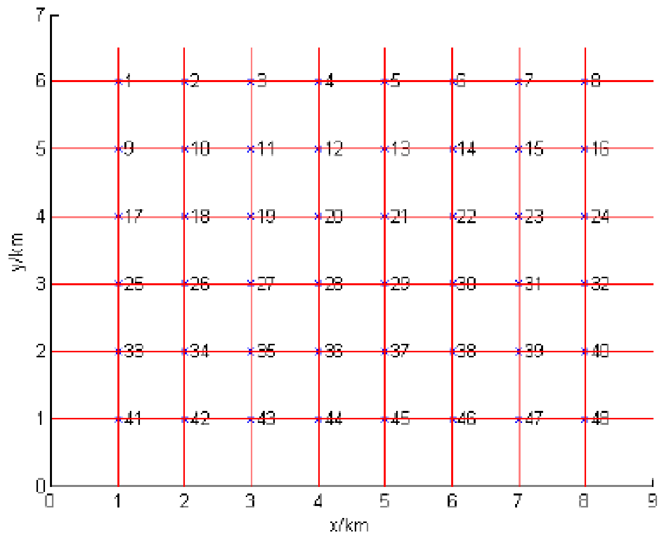

Figure 8. Road network structure diagram

The objective function and constraint conditions are established with the lowest annual travel cost of the car owner, the genetic algorithm is used to solve the model, the optimal location is obtained, and the initial location and capacity library is formed. The location service range division and the optimal location service range division are shown in Figure 9 where: the box represents the location of the charging station site, and the asterisk represents the charging demand point.

Taking the lowest user travel cost as the site selection model, each scheme that meets the range of the number of charging stations is optimized for site selection [8], and the objective function value is calculated to determine the initial site selection and fixed capacity library, where The optimal cost values of different schemes are shown in Figure 10.

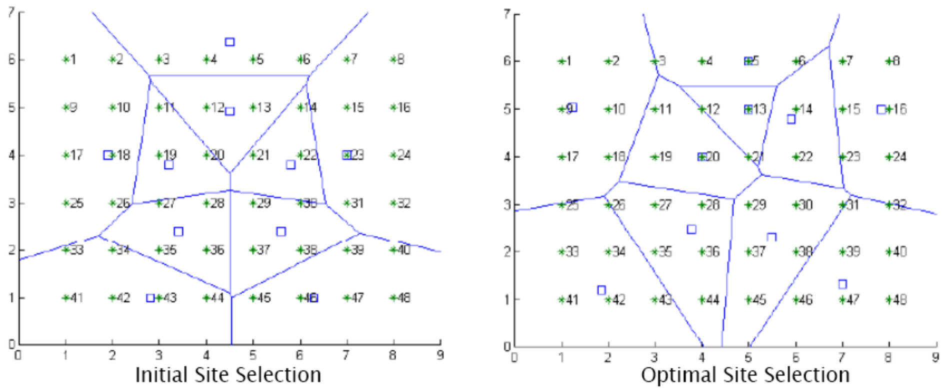

Figure 9. The service scope division map of initial location selection and optimal location of charging stations

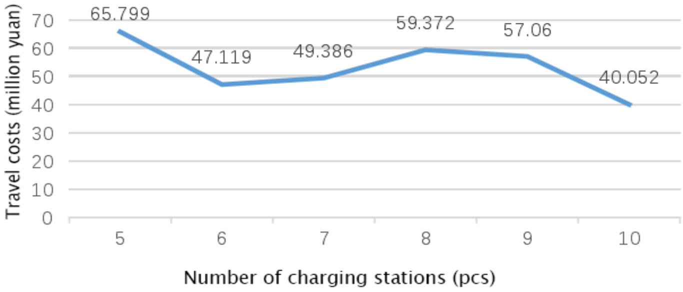

Figure 10. The annual travel cost of electric vehicle owners in each scheme

The specific location coordinates and capacity configuration of the optimal solution are shown in Table 3.

Table 3. The specific location coordinates and capacity configuration of the optimal solution

Numbering	quantity	Abscissa	Y-axis
1	53	1023	556
2	26	1123	43
3	34	965	568
4	41	898	456
5	twenty three	966	565
6	66	1123	365
7	41	1200	864
8	53	1142	664
9	42	1312	754
10	63	967	696

5. The best solution for charging and battery swapping

5.1. Monte Carlo Simulation

In this paper, the Monte Carlo method is used to sample and simulate the charging situation of electric vehicles [9], the distribution of electric vehicle charging load in three different regions can be obtained, and the charging load of the three functional areas can be superimposed to obtain the total charging load of electric vehicles in a certain area in a certain day in the future.

5.2. Solution of the model

According to the set parameters, the Monte Carlo method is used to simulate the load curves of three different functional areas and the comparison diagram of the total charging load curve of the electric vehicle obtained by superposition is shown in Figure 11.

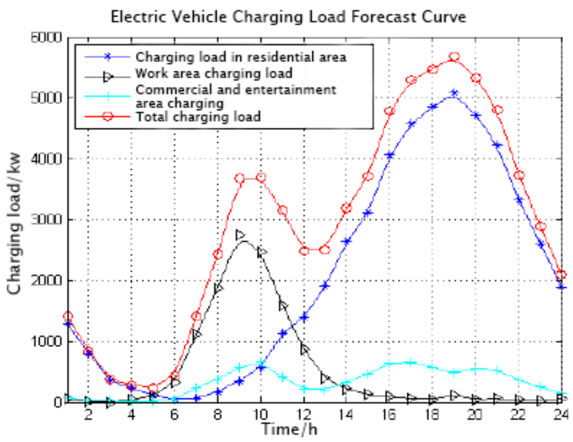

Figure 11. Prediction map of spatiotemporal distribution of electric vehicle charging load

The predicted value of the total charging load of electric vehicles is shown in Table 4.

Table 4. Predicted value of total charging load of electric vehicles

Day	Weekend	Arrival	Charge. Duration	Idle. Duration	Park. Duration	Energy	data
Wednesday	0	4.13	133.1	-1	132.1	7.932	caltech
Wednesday	0	6.75	179.0833	492.0167	671.1	10.013	caltech
Wednesday	0	6.75	65.9	493.0167	558.9167	5.257	caltech
Wednesday	0	7.62	88.26667	470.2	558.4667	5.177	caltech
Wednesday	0	7.67	179.9333	322.7	502.6333	10.119	caltech
Wednesday	0	7.72	94.63333	539.0333	633.6667	7.91	caltech
Wednesday	0	7.78	220	0.15	220.15	15.294	caltech
Wednesday	0	7.97	110.0667	138	248.0667	6.953	caltech
Wednesday	0	8.17	57.06667	127.8333	184.9	2.174	caltech
Wednesday	0	8.2	198.15	-0.98333	197.1667	2.439	caltech
Wednesday	0	8.23	199.2333	0.166667	199.4	6.955	caltech
Wednesday	0	8.23	63.5	607.8667	671.3667	3.249	caltech
Wednesday	0	8.23	87.18333	430.8333	518.0167	2.72	caltech
Wednesday	0	8.33	46.75	461.85	508.6	2.575	caltech
Wednesday	0	8.5	204.4333	52.9	257.3333	5.4	caltech
Wednesday	0	8.52	175.25	390.3	565.55	4.929	caltech
Wednesday	0	8.55	136.0167	412.4833	548.5	4.043	caltech

Figure 12 is a comparison chart of the distribution of the total load of the power grid under different penetration rates of electric vehicles.

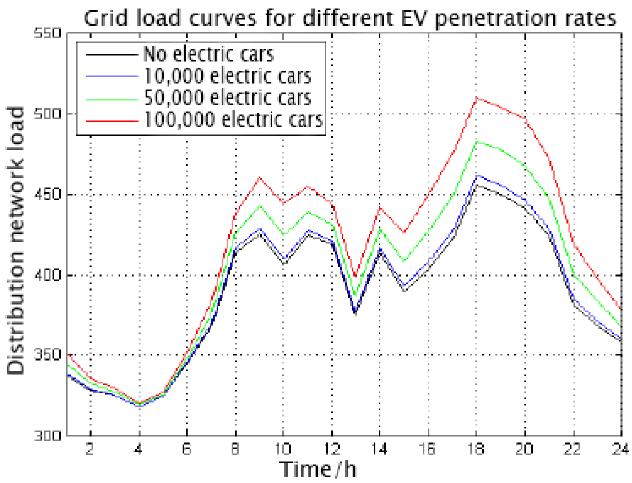

Figure 12. Predicted load curve of power grid under different penetration rates of electric vehicles

As can be seen from Figure 12, with the increase of the penetration rate of electric vehicles, the overall load of the power grid gradually increases, and the load curve of the power grid presents an obvious peak-to-valley difference. Therefore, a large number of electric vehicles connected to the grid will have a series of negative impacts on the grid [10]. In the follow-up research, on the basis of load forecasting, it is of great significance to further study the site selection and planning of electric vehicle charging stations.

6. Conclusion

In this paper, we study the problems of electric vehicle charging stations and use quantum particle swarm optimization algorithm, fuzzy inference algorithm and multi-objective optimization to solve the problems of optimal charging pile location and its quantity distribution, spatial and temporal distribution of user charging demand, gradual expansion or reduction of charging piles, and optimal scheme of charging and power exchange respectively, which have certain engineering practical significance.

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