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Non-dominated sorting WOA electric vehicle charging station siting study based on dynamic trip chain

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ABSTRACT

The travel behavior of electric vehicle (EV) users is highly random, and the interests of EV charging station investors interact with the needs of charging users. The increasing number of electric vehicles (EVs), cities have higher requirements for EV charging station location planning. This paper proposes a multi-objective EV charging station siting method based on trip chains. First, the EV trip chain is used to analyze its dynamic travel process, construct probabilistic models, and simulate its charging behavior using Monte Carlo (MC) method to obtain the time–space distribution of EV users' charging demand. Then, the Whale Optimization Algorithm (WOA) and the Non-dominated Sorting Whale Optimization Algorithm (NSWOA) are used to solve problems that aim to optimize the cost for the investor and improve user satisfaction as objective functions. Finally, taking a region in Nanjing as an example, the simulation concluded that multi-objective siting planning optimizes the investor cost by 9.22% compared with single-objective siting planning, reduces the user's station-seeking time by 47.91%, charging waiting time by 65.83%, which verifies the method has the advantages of optimizing the investment cost and enhancing the user's satisfaction, and it provides decision-making ideas for the study of EV charging station siting and layout.

1. Introduction

In recent years, EVs have gradually become an important alternative to traditional fuel vehicles due to their advantage of not emitting pollutant gases, and have been rapidly promoted worldwide, as shown in Fig. 1, which shows the trend of changes in the global ownership of EVs. However, with the increasing number of EV users, there is a growing imbalance between their infrastructure construction [1], leading to the frequent occurrence of phenomena such as the difficulty of finding piles for EVs in certain areas [2], so EV charging stations, as an important part of the infrastructure of EVs, the planning and construction of which is of great significance to the popularization of EVs [3]. According to the *Guiding Opinions on Further Building a High-Quality Charging Infrastructure System* issued by the General Office of the State Council of China, the charging infrastructure construction in China should be based on the principle of "scientific layout and moderate overrun" [4], Therefore, how to scientifically plan the layout of EV charging stations has become an important research direction to accelerate the integration of transportation and energy, meanwhile help "carbon-neutral".

Scholars in various countries have achieved many results in the siting of EV charging stations. Literature [5] establishes an EV charging station siting model with the objective of minimizing the cost of charging stations and the economic loss to users. The time–space distribution of EVs in a region is studied based on the historical data of EV stock, and then realizes the scientific layout of charging stations. Literature [6] proposes a Mixed-integer nonlinear optimization method for optimizing the layout and size of fast charging stations, considering the cost of charging station exploitation. Literature [7] conducts a siting study with the objective function of minimizing the overall social cost includes the cost of power loss during EV travel and the cost of network loss in the distribution network. In addition to considering the economic costs, traffic flow is also one of the key factors to be considered in the scientific layout of charging stations Literature [8] analyzes the characteristics of changes in the number of vehicles in residential, work, and commercial areas during different time periods and addresses the problem of traffic congestion caused by charging queues. Literature [9] proposes an optimization planning

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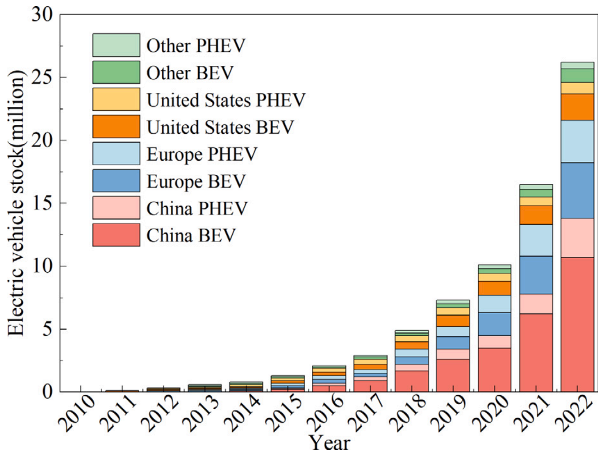

Fig. 1. Global EV stock 2010–2022.

method for public charging stations based on the spatial distribution of traffic flow, by comprehensively considering the characteristics of urban traffic flow distribution and the operational constraints of the power distribution network. The popularization and development of EVs not only depend on the scientific layout of charging stations, but also require consideration of the normal operation of the distribution network. Literature [10] establishes an evaluation model for minimum network loss, minimum load fluctuation rate, and minimum voltage deviation index of the distribution network, and then combines it with the traffic network model to achieve a station construction plan that has the least impact on the operation of the distribution network. Literature [11] establishes a probabilistic model of charging load demand for multiple types of EVs by studying the charging characteristics of different types of EVs and analyzes how to reduce the load impact brought by EV charging to the distribution network. Literature [12] studies how EV can scientifically access the distribution network to achieve the purpose of peak shaving and valley filling with the premise of reducing load fluctuation of the distribution network, and with the optimization objectives of reducing user charging cost and peak–valley difference of the distribution network load.

In terms of charging load prediction, literature [13] proposes an urban charging load prediction model with a real-time simulation input interface, which fully considers the impact of EV locations and the occupancy status of public charging facilities on EV charging behavior, achieving accurate load prediction. Literature [14] presents a spatiotemporal prediction model for EV charging load under the "EVs-Traffic-Distribution" mode. It establishes an individual EV charging model and a road traffic model that considers the characteristics of traffic network topology, the speed-flow relationship, and regional attributes, and then conducts charging load prediction. Literature [15] introduces the concepts of road segment impedance and node impedance in load forecasting, fully considering the time-varying characteristics of traffic information and the impact of intersections on EV travel. To improve prediction accuracy, Literature [16] proposes a charging load prediction model based on an improved random forest regression (RFR) algorithm enhanced by the sparrow search algorithm (SSA). Literature [17], from the perspective of vehicle ownership, uses the GM(1,1) model to estimate this factor and further predicts the load demand for EVs connected to the grid.

The main methods currently used for solving the site selection model are exact algorithms, heuristic algorithms, and deep learning algorithms. Literature [18] investigates the multi-stage stochastic problem of EV fast charging station siting under demand uncertainty and employs the Benders decomposition algorithm to solve, it is found to outperform a stand-alone mathematical planning solver in solving this type of problem, but the method is unable to handle the siting problem considering charging station capacity constraints and congestion. Literature [19] combines the particle swarm optimization (PSO) algorithm with the direct search method, which ensures its convergence and accuracy while solving the results quickly. Combining the PSO algorithm with other algorithms or improving the PSO algorithm is a commonly used method to study the charging station siting at present. Literature [20] proposes a recurrent neural network algorithm integrated with the firefly algorithm, which improves the global optimization capability for effective charging station siting and capacity setting purposes. Although deep learning algorithms can effectively solve the complex charging station siting problem in reality, that required data size is large, training time is long, and the model is unstable.

Based on this, this paper attempts to use ArcGIS software and the open-source mapping platform OSM (Open Street Map) to obtain the road network of the study area, after that combines it with the trip chain theory and the MC method to construct an EV charging load forecasting model. This model is used to obtain EV trip data and charging data. By combining the trip chain theory with the MC method, it fully considers the highly random nature of EV travel behavior [21], and the load forecasting model addresses the difficulty in obtaining EV travel and charging historical data. In addition, the application of ArcGIS makes this research method more practical. Based on the data obtained from the charging load forecasting model and relevant constraints, this paper also establishes a multi-objective EV charging station location model with the objectives of minimizing the charging station investment cost and maximizing user satisfaction, intuitively solving the imbalance between the investment cost for charging station investors and EV user satisfaction. When solving the location model, considering that exact algorithms cannot handle location problems with related constraints and that traditional PSO algorithms have low solution efficiency, so heuristic algorithms WOA and NSWOA are used to improve the efficiency and accuracy of solving the model. In summary, this paper proposes an NSWOA-based method for locating EV charging stations based on dynamic trip chains, addressing some existing issues in related research and providing a research approach for charging station location.

The main work and innovations are the following:

- Considering the randomness of user travel, statistical characteristics of EV travel chains at the group level were analyzed using large sample data to describe the dynamic travel process and user charging behavior. A probabilistic model was then developed, and MC simulations were employed to determine the spatiotemporal distribution of charging demand, which maximally reflects the autonomy of user travel and charging behavior.
- Aiming to balance the investment cost for investors and the convenience needs of users, the layout planning of charging stations was studied. The study mainly considered the impact of economic factors such as land costs, infrastructure construction costs, and operating costs, as well as user convenience needs, on the layout of fast-charging stations. A multi-objective site selection planning model was proposed, which minimizes the total investment cost from the investor's perspective while maximizing user satisfaction.
- Taking a certain area in Nanjing as an example, the road network node map was obtained via ArcGIS and OSM. Based on the established model, WOA and PSO were applied to solve the single-objective planning model, while NSWOA and Multi-Objective Particle Swarm Optimization (MOPSO) were adopted to solve the multi-objective planning model. By analyzing the investment costs and user charging convenience, the feasibility of the proposed method was verified, and it was also demonstrated that NSWOA performed well in the research on the site selection of EV charging stations.

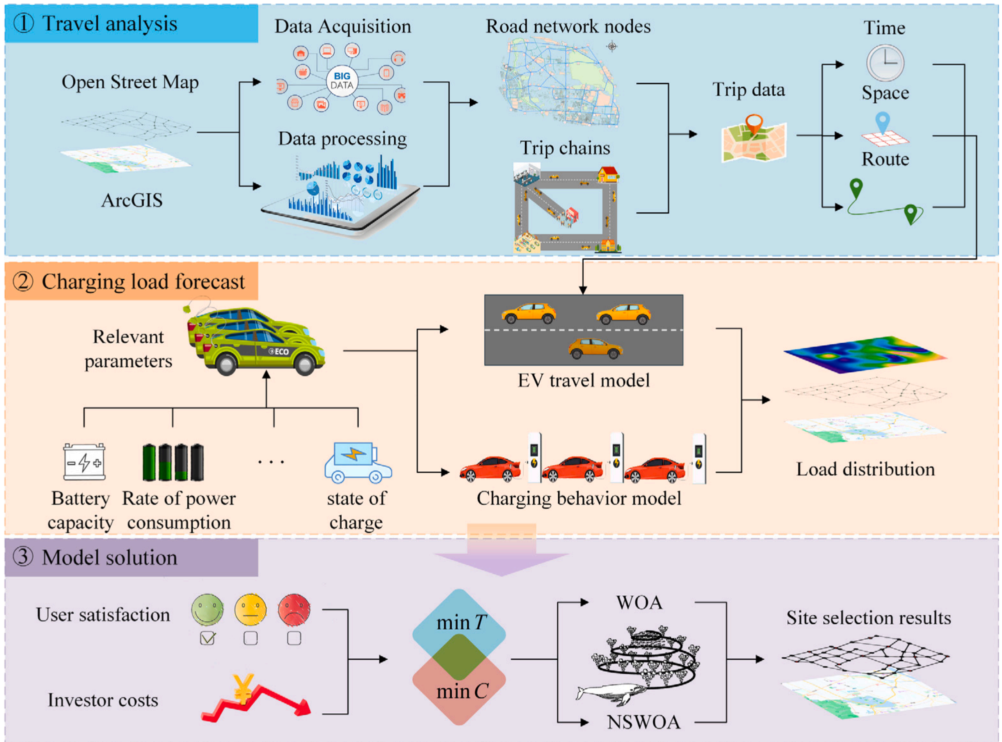

Fig. 2. Technological route.

The rest of this paper is structured as follows: Section 2 analyzes the travel chains of EVs and user charging behavior, utilizing MC simulations to construct a charging load prediction model. Section 3 establishes the objective functions. Using the travel and charging data from Section 2, a multi-objective location model for EV charging stations is developed, taking relevant constraints into account. Section 4 includes a case study for validation. Finally, Section 5 concludes the work. The technical route of the work done in this paper is shown in Fig. 2.

2. EV charging load prediction model

The modeling of EV users' travel and charging behaviors is affected by many factors, such as time-characterized variables, space-characterized variables, EV state of charge, and charging users' mileage anxiety. Based on the analytical description of these key factors, this paper establishes a complex dynamic system to simulate the charging behavior of EV users and predicts their charging load demand.

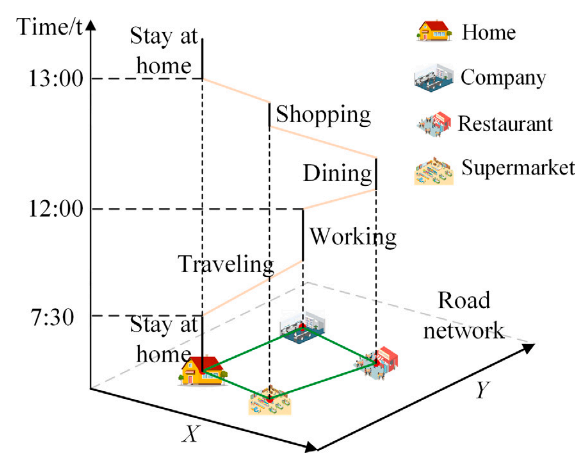

Fig. 3. Three-dimensional space–time representation of travel behavior.

2.1. Trip chain analysis

There are many uncertainties in the analysis of EV users' travel behavior, which includes key factors such as origin and destination, departure time, arrival time at destination, and distance traveled [22], so this paper proposes to use the trip chain theory to describe and analyze it. The trip chain is a detailed description of the entire process of traveling, for example, a user leaves home at 7:30 in the morning, arrives at work by driving EV, leaves the company at 12:00 to go to a restaurant for a meal, then goes to the supermarket on the way home, and arrives back at home at 13:00, which is a complete chain of trips. This process contains spatial–temporal information, transportation modes and other travel characteristics, a comprehensive and coherent description of the user's travel process in this period. As shown in Fig. 3, it is a spatio-temporal expression of this user's travel behavior during this time. So, for the EV travel process, the process of departure, driving, arrival, stopping, and leaving is completed during the private EV travel process [23], and the repetition of this process forms the EV trip chain.

In order to make this method more feasible, this paper establishes a probabilistic model for each feature quantity in the trip chain by statistical characterization at the group level with large samples [24]. The referenced data is from the National Household Travel Survey (NHTS) household travel statistics from 2009 and 2017 [25].

Regarding the division of travel destinations, according to existing studies, this paper classifies them into five types, as shown in Table 1. By studying the data of users' round-trip journeys in one day, it was found that the average value of the trip chain length of private EVs was 3.02 [26], When it is greater than this value, it can be determined that there is a short stop on the way and that the probability of charging behavior occurring during this process is extremely low. So, this paper divides the trip chain on the basis of the trip chain length of 3, as shown

Table 1
Destination classification.

Destination	Residential areas	Workspace	Recreation area	Shopping areas	Other
Symbol	H	W	SR	SE	O

Table 2
Segmentation of the trip chain.

Number	Trip chain
1	H-W/SR/SE/O-H
2	H-W-SR/SE/O-H
3	H-SR-W/SE/O-H
4	H-SE-W/SR/O-H
5	H-O-W/SR/SE-H

in Table 2, and it is also set that charging behavior will not occur in the above cases.

The study shows that the time of the first daily trip T for EVs follows a normal distribution. obey a normal distribution, $\mu_T = 6.92$, $\sigma_T = 1.24$, The probability density function is:

$$f_{T0}(T) = \frac{1}{\sqrt{2\pi\sigma_T^2}} \exp\left[-\frac{(T-\mu_T)^2}{2\sigma_T^2}\right], 0 < T \leq 24 \tag{1}$$

EVs do not stay for the same amount of time in different travel destinations, so the dwell time of EVs in each of the several regions delineated in this paper herein obeys the following probability density function. The residence time density function in the H-region is as follows:

$$f\left(t_i^p\right) = \frac{\alpha}{c}\left(\frac{t_i^p}{c}\right)^{\alpha-1} e^{-\left(t_i^p/c\right)^\alpha} \tag{2}$$

where, α represents the shape parameter, and c represents the scale parameter.

The stay time in area W and other areas follows this probability density function, as show in Eq. (3):

$$\begin{cases} f_{t\_p}(p) = \frac{1}{a}e^{-(1+bp)^d}(1+bp)^{d-1} \\ p = \frac{t_i^p - \gamma}{a} \end{cases} \tag{3}$$

where, t_i^p is the length of time the EV stays at destination i, and the values of the parameters a, b, d, γ are obtained through experimental fitting.

The above is a probabilistic model of the time-characterized variables in the study of the EV trip chain. In addition to this there are space-characterized variables that need to be analyzed.

The single trip distance, d_i is denoted as the distance traveled by the EV from the destination $i-1$ to the destination i, and its probability density function is as follows:

$$f_d(d) = \frac{1}{d\sigma_d\sqrt{2\pi}} \exp\left[-\frac{(\ln d - \mu_d)^2}{2\sigma_d^2}\right] \tag{4}$$

where, $\mu_d = 2.29$, $\sigma_d = 0.9$.

The space transfer probability, denote D_i as the type of the travel destination i, p_{ij} as the probability that an EV transfers from destination i to destination j, $i \in [HWSRSEO]$, $j \in [HWSRSEO]$, then the probability matrix for the space transfer probability of the EV is:

$$p_{ij} = \begin{bmatrix} p_{11} & \cdots & p_{15} \\ \vdots & \ddots & \vdots \\ p_{51} & \cdots & p_{55} \end{bmatrix}, \begin{cases} 0 \leq p_{ij} \leq 1 \\ \sum_{i=1}^{5} p_{ij} = 1 \end{cases} \tag{5}$$

2.2. Charging behavior analysis

Whenever a user arrives at a destination, whether the user chooses to charge is affected by various factors, and this paper analyzes the user's charging behavior mainly based on the state of charge (SOC) of the EV in the simulation process. EV charging termination states follow an exponential distribution [27], Let S_i be the SOC at arrival at destination i. Then S_0 can be described by the distribution of charge termination state of charge, its probability density function is as follows:

$$f_S(S) = \begin{cases} \lambda_s S^{\lambda_s - 1} & , 0 < S \leq 1 \\ 0 & , \text{otherwise} \end{cases} \tag{6}$$

where, the parameter $\lambda_s = 4.352$.

EV users suffer from mileage anxiety in most of them [28], so they tend to choose to recharge when the power level is below a certain value, but there are individual differences in this power level. In order to facilitate the study of this paper, the concept of the lowest SOC preference, i.e. the lowest SOC of the battery that is acceptable to the user, its probability density function is as follows:

$$f_{s\_M}(s) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left[-\frac{(s-\mu_s)^2}{2\sigma_s^2}\right] \tag{7}$$

where, $\mu_s = 0.47$, and $\sigma_s = 0.18$.

In the study of this paper, the EV arrives at the destination i with two situations of SOC S_i, as shown in Eq. (10), one is charged at the destination $i-1$ and the other is uncharged as follows:

$$S_i = \begin{cases} S_{i-1} - \frac{\lambda \cdot d_i}{P_c} & , \text{uncharged} \\ S_{i-1} + \frac{p_f \cdot t_{i-1}^c}{P_c} - \frac{\lambda \cdot d_i}{P_c} & , \text{charged} \end{cases} \tag{8}$$

where, p_f is the power of the fast charger and t_{i-1}^c is the charging duration at the destination $i-1$.

There are also two states to be considered with respect to the charging duration, if the charging is not completed at the destination i, the charging time can be expressed in terms of the dwell time t_i^p at the location i, and if it is fully charged, as shown in Eq. (9):

$$t_i^c = \begin{cases} t_i^p & , \text{not full} \\ (P_c - EL_i)/p_f & , \text{full} \end{cases} \tag{9}$$

where, P_c is the capacity of the battery, and EL_i is the remaining power of the EV when it reaches destination i.

2.3. Charging load prediction

Based on the above analysis of user travel behavior and charging behavior, meanwhile, in order to make the charging demand prediction results more in line with the actual situation, so this paper uses MC to simulate the charging process of its traveling with the following steps, and the simulation flow is shown in Fig. 4.

Step 1: Input planar coordinate data, time-characterized variables, space-characterized variables, and probability density function of charging behavioral features.

Step 2: Determine the total number of vehicles N, initialize $n = 1$.

Step 3: Initialize EV vehicle status, select the starting departure location, initial SOC, minimum SOC preferences and the time of the first trip, $i = 1$.

Step 4: Select the type of trip chain of the vehicle n randomly.

Step 5: Select the travel destination and length of stay for travel i randomly.

Step 6: Calculate the power consumption during trip i, and then determine whether to charge or not at this moment based on the SOC when arriving at destination i and the vehicle's lowest charge state preference. If charging is selected, calculate the charging time at the location i, output the charging data, and then execute step 7. If charging is not selected, step 7 is executed directly.

Step 7: Determine whether the destination i is the end point, if it is, execute step 8, if not, after reaching the destination i, calculate the travel time and arrival time according to the travel distance and travel speed, then update the SOC when arriving at the destination i according to Eq. (8). $i = i + 1$, perform step 5 again.

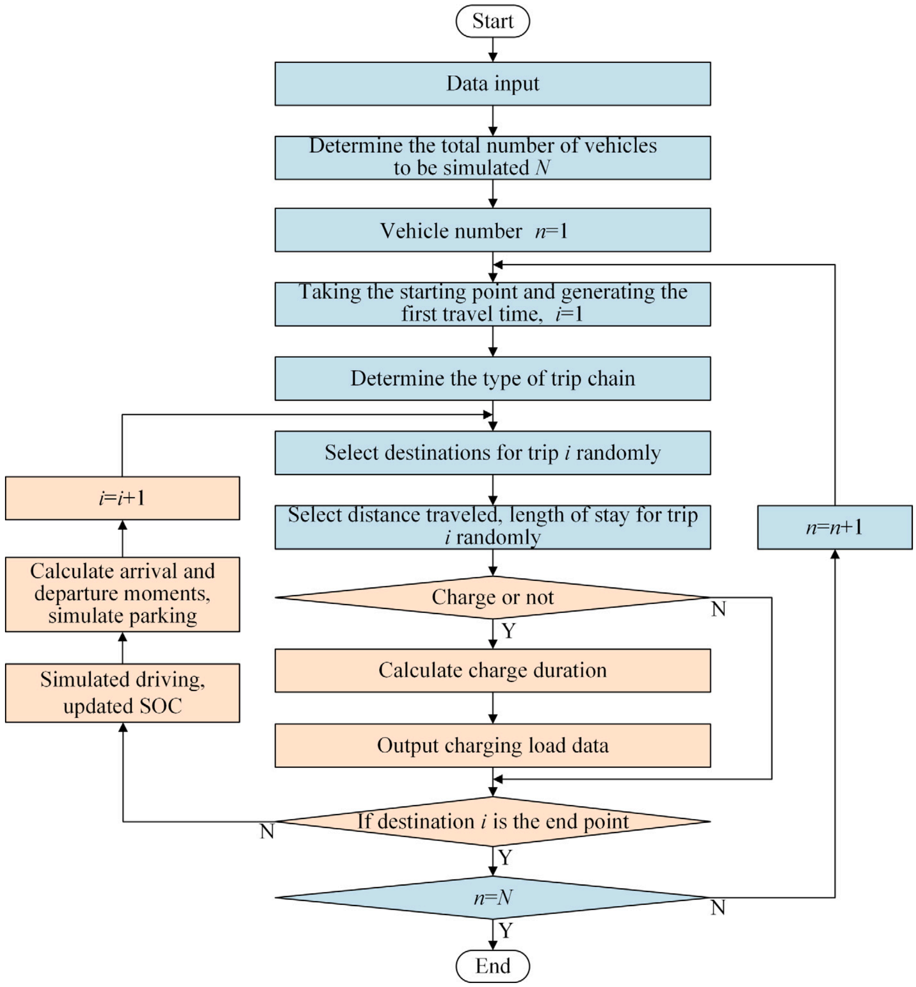

Fig. 4. MC simulation of charging demand flowchart.

Step 8: Determine whether $n = N$ is valid, if it is valid, it means that the simulation of charging demand for all private EVs has been completed, end the whole simulation process, if not, then return to step 3.

3. Multi-objective location model for EV charging stations

This section primarily establishes the objective function for the location planning of EV charging stations, considering relevant constraints to ensure that the charging stations can provide normal charging services. Finally, a multi-objective location model is established to achieve optimal location and sizing of EV charging stations.

3.1. Objective function

We exclude private charging stations from our consideration, focusing primarily on urban public fast charging stations as the subject of our research. For the planning and construction of fast charging stations, it mainly involves two key stakeholders: the investors and the users. When selecting the location, both the economic costs of the investors and the service experience of EV users need to be considered. Regarding the economic costs for investors, the main considerations include land costs, infrastructure construction costs, and operational costs, with the objective function being established to minimize the total investment cost. As for the service experience of EV users, it is characterized by the time spent searching for a station and the waiting time of users, with the goal of minimizing the total search distance and reducing waiting time. We construct a multi-objective location planning model for fast charging stations by considering both aspects. In order to make the final station construction planning can achieve the goal of minimizing the investors' total cost and maximizing user satisfaction, this paper through search for information to find out the specific composition of the investment cost of charging station [29], to construct the total investment cost objective function; A user satisfaction objective function was constructed based on the travel data and charging data obtained from the charging demand forecasting work.

At present, urban land resources are scarce, and most of the charging stations are constructed by renting parking spaces, so the land cost mainly depends on the rent of parking spaces [30]. Therefore, assuming the cost of land j for charging stations is c_j^1, q_j is the number of charging piles at charging station j, and c_r is the rent for a single parking space, the cost of land can be expressed as follows:

$$c_j^1 = q_j c_r \tag{10}$$

Let the infrastructure cost be c_j^2, which includes three components [31]: distribution system cost A, charging system cost B, and monitoring system cost C, as shown in Eq. (11)

$$c_j^2 = A + Bq_j + C \tag{11}$$

Define the operational cost of the charging station as c_j^3, which primarily encompasses the daily maintenance costs associated with its operations. This paper establishes the operational cost of the charging station based on its infrastructure cost as follows:

$$c_j^3 = \eta c_j^2 \tag{12}$$

where η is the conversion factor between operating costs and infrastructure costs.

In summary, considering the large upfront investment cost of constructing charging stations and the changing value of cash flows over time, a discount rate is introduced to measure the value of cash flows in different periods. The discount rate is set to be r_0, the operating life is set to be k, and based on the discounted cash flow values, the investment cost minimization function is formulated as follows:

$$\min C = \sum_{j\in J}\left(c_j^1 X_j + c_j^2 X_j + c_j^3 X_j\right)\left[\frac{r_0\left(1+r_0\right)^k}{\left(1+r_0\right)^k-1}\right] \tag{13}$$

where X_j is the decision variable as shown in Eq. (16):

$$X_j = \begin{cases} 1 & \text{, build station at j} \\ 0 & \text{, no station at j} \end{cases} \tag{14}$$

In order to improve the user charging experience, this paper constructs a user satisfaction maximization objective function based on station-seeking time and user waiting time in queue.

If an EV is charged at point j from i, the station-seeking time can be expressed as follows:

$$t_{ij} = \frac{\sqrt{\left(X_i - X_j\right)^2 + \left(Y_i - Y_j\right)^2}}{v} \tag{15}$$

The number of EVs going to charge station j at demand point i be m_i, then the total station-seeking time for EVs going to charge station j is as follows:

$$T_{ij} = \sum_{i\in I} t_{ij} m_i \tag{16}$$

In the actual charging, not every vehicle will be charged to 100%, and it is found that when the power is lower than 20%, most of the users will choose to charge, and when the power reaches 80% the users will have a high probability to terminate the charging, the range of the charging amount is represented by β, so the queuing time of a single charging station T_m is as follows:

$$\begin{cases} T_p = \beta t \\ T_m = T_p \left\lceil \frac{m_i}{q_j} \right\rceil \end{cases} \tag{17}$$

Then the user waiting time for all charging stations is as follows:

$$T_w = \sum_{i\in I}\sum_{j\in J} T_m Y_{ij} \tag{18}$$

where Y_{ij} is the decision variable as shown in Eq. (19):

$$Y_{ij} = \begin{cases} 1 & \text{, users choose point j for charging} \\ 0 & \text{, users do not choose point j for charging} \end{cases} \tag{19}$$

In summary, considering that the minimum function of the operator's input cost is in terms of years, the following function is established with the objective of maximum user satisfaction:

$$\min T = \left(\sum_{i\in I}\sum_{j\in J} T_m Y_{ij} + T_{ij}\right) \times 365 \tag{20}$$

In order to visualize the planning results, the average user station-seeking time and average user queuing time will be used in the simulation results to indicate the user satisfaction.

3.2. Restrictive condition

The service capacity of charging stations is limited, and if numerous EVs are connected to the grid at the same time, it will bring a shock to the grid operation, which will lead to the inability of the grid to operate normally [32]. Therefore, this paper puts the following constraints on the construction planning of charging stations to ensure that there will be no negative impact on the grid operation after the charging stations are built.

(1) Number of charging piles

For the construction of centralized charging stations, there is generally a minimum number of piles in terms of the deployment of charging piles [33], and unlimited pile construction is not possible due to the limited number of parking spaces at alternative sites, so $q_{min} = 3$, $q_{max} = 15$.

(2) Charging station service capacity

There are a limited number of charging piles within a single charging station, so it is not possible to serve an unlimited number of users with a limited service capacity as shown in Eq. (21):

$$\sum_i m_i Y_{ij} \le T q_j / t, \forall i \in I, j \in J \tag{21}$$

(3) Charging demand and charging station construction constraints

Charging facilities will not be deployed at sites that are not selected as alternative sites for charging station construction, which is constrained in this paper as follows:

$$Y_{ij} \le X_j, \forall i \in I, j \in J \tag{22}$$

(4) Station-seeking distance constraints

When a user generates a demand for charging at a certain destination, the distance the user can travel in this SOC is limited, so station-seeking distance should not exceed the maximum station-seeking distance of EV as follows:

$$d_{ij} \le d_{\max}, \forall i \in I, j \in J \tag{23}$$

To facilitate solving the model in this paper, default that all users who generate charging demand at the demand point will go to the same charging station for charging. This means that all users at the same point of demand will choose to go to the optimal charging station based on their location.

3.3. Model solving

The model includes the investment cost minimization objective function Eq. (13), the user satisfaction maximization objective function Eq. (20), the constraints Eqs. (21)–(23), and the limitation on the number of charging piles within the station. It aims to minimize costs for investors while ensuring maximum user satisfaction. While seeking a balance between the two, the model also considers the service capacity of the charging station and the mileage anxiety of EV users. Therefore, solving this model constitutes a mixed-integer nonlinear programming problem. To obtain the optimal layout plan for the charging station, precise and efficient solutions are required. The exact algorithm consideration is too single, and the traditional algorithms such as PSO have the problem of low convergence accuracy in solving this model [34]. So the WOA was chosen to solve the model, which finds the optimal solution by imitating the search process of whales catching food in the ocean. And this algorithm has the characteristics of simple structure and few parameters of itself, which is faster and more accurate than the traditional PSO algorithm and genetic algorithm in multivariate function solving [35].

Thus, in this part of the model solution, the traditional WOA was first used to solve the single-objective model for the siting model constructed in this paper to derive the planning scheme for the charging station under the consideration of the single-objective. However, for function problems with multiple optimization objectives, among multiple objective function values which corresponding to whale individual

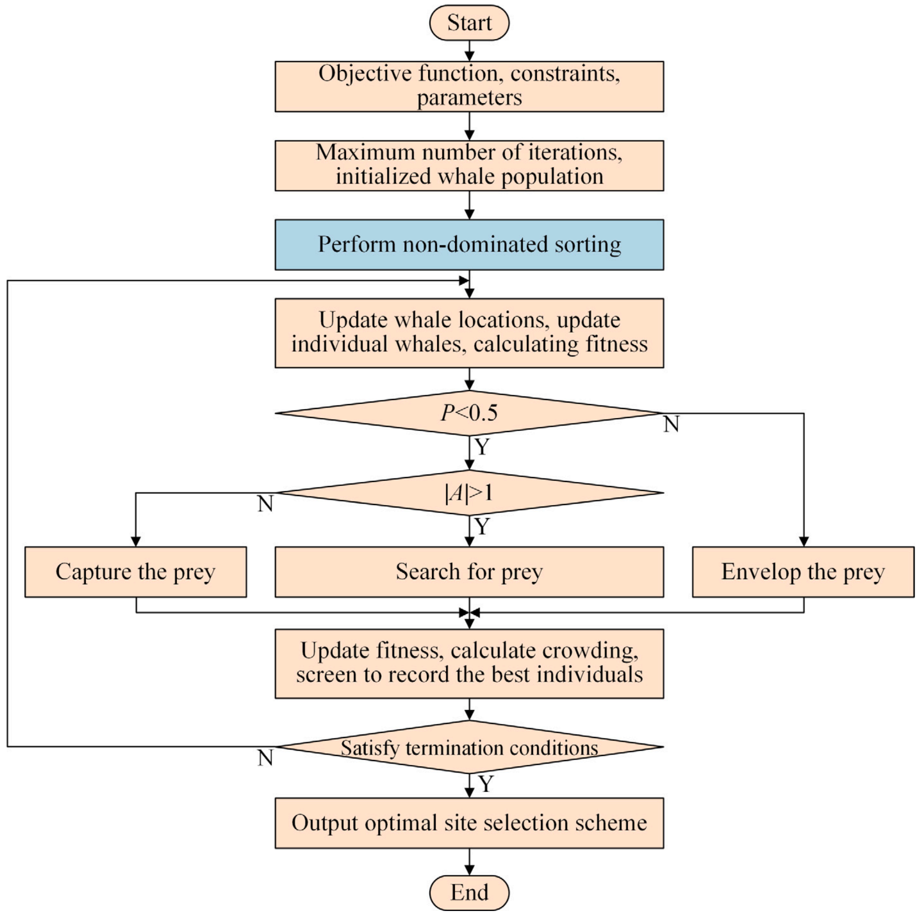

Fig. 5. Model solving flowchart.

has conflict, the inability to deal with the relationship among each objective function values leads to the WOA being unable to deal with this type of problem [36]. In order to deal with the multi-objective model, a process of sorting populations according to on-dominated sorting was added to the traditional WOA. Through crowding calculation and elite retention strategy, screen out the best non-dominated individuals to guide the population and evolve the population, This gives the algorithm the ability to be able to solve multi-objective optimization problems [37]. As shown in Fig. 5, it is a flowchart for solving the multi-objective model of this paper with the following steps:

Step 1: Input parameters such as objective function, constraints, initialize whale population size, maximum number of iterations.

Step 2: Generation of a first-generation whale population, followed by merging of the current generation with the newly generated generation.

Step 3: Calculate the non-dominated rank of all individual whales in the combined group and rank them from smallest to largest.

Step 4: In the order of step 3, calculating the crowding size of the individuals with the same non-domination rank, and sorting the individuals with the same rank from the largest to the smallest crowding size.

Step 5: Based on the sorting results of steps 3 and 4, screen the maximum value as excellent individual, and record the location information of the optimal whale individual.

Step 6: Determine whether the maximum number of iterations is reached, if yes, output the optimal siting scheme, otherwise return to step 2.

4. Case validation

This section takes a specific area of Nanjing as an example to simulate and predict the EV charging load using its road network system. Based on the obtained data and relevant constraints, a charging station location model is constructed. The WOA and the NSWOA algorithm are used to solve the single-objective and multi-objective models, respectively. Additionally, PSO and MOPSO are employed to solve the results, and a comparison is made between them. The feasibility of this method is verified by the result analysis, which can provide certain ideas for the study of EV charging station siting layout research. The platform used for simulation is ArcGIS and MATLAB R2023b.

4.1. Data acquisition

The simulated road network was obtained from OSM (Open Street Map) open-source mapping website to obtain the road vector data in the study area and imported into ArcGIS for analysis. Firstly, the vector data obtained from OSM are processed and analyzed, and then according to the data attribute table, the irrelevant sections such as sidewalks and parkways are eliminated, the main arterial roads where EVs pass through are retained, and the two-way lanes are merged, and the processing process of road network node diagram is shown in Fig. 6, and the final road network of the simulation area obtained is shown in Fig. 7. The area has a total area of approximately 77.39 km^2, with an east–west span of 10.9 km and a north–south span of 7.1 km. Considering the road network nodes as demand points, there are a total of 47 demand points, and these demand points are classified into five types of zones based on their actual locations, as shown in Table 3. In order to facilitate the model processing in this paper, the road node maps obtained after ArcGIS processing are mapped to the plane rectangular coordinate system for processing, and the relevant parameters are set according to the real data.

Table 3
Nodal area division.

Area	Nodes
H	1, 2, 13, 21, 26, 29, 33, 35, 44
W	3, 8, 14, 16, 24, 32, 34, 39, 40, 46
SR	5, 6, 11, 17, 20, 22, 31, 42, 45, 47
SE	4, 9, 12, 15, 19, 23, 27, 37, 41
O	7, 10, 18, 25, 28, 30, 36, 38, 43

Table 4
Parameter values for Eq. (3).

Parameters	a	b	d	γ
W	164.51	−0.23	4.35	438.45
Other	41.76	0.66	−1.52	68.52

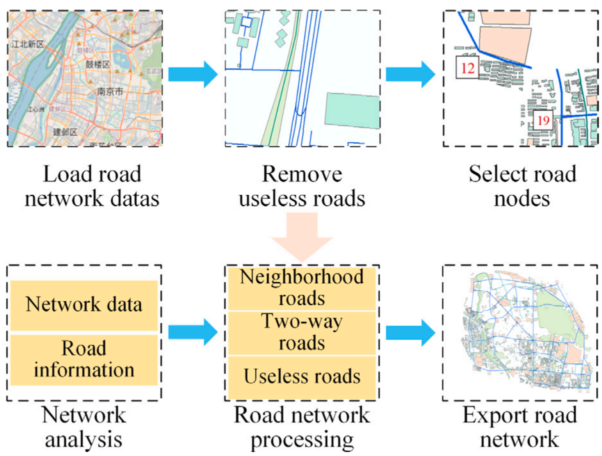

Fig. 6. ArcGIS road network process.

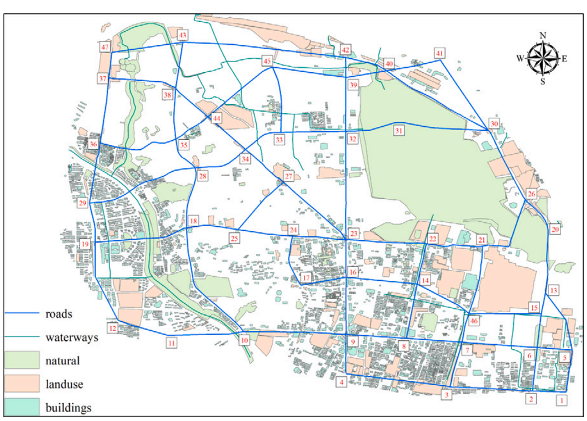

Fig. 7. Nodal map of the road network in the simulation area.

When conducting travel chain analysis, the parameters of the probability density function for stay time in W district and other districts are derived from analyzing and fitting the survey data from the National Household Travel Survey (NHTS) for 2009 and 2017, as shown in Table 4.

The number of EV in the region is set to be 5000, assume that each road has the same vehicular traffic, and the charging power of the charging station is kept constant. In this paper, without considering the effect of traffic congestion on the road on the speed and power consumption of the vehicle, the vehicle consumes the same amount of power per kilometer and travels at a constant speed on the road. Summarized through numerous literature review, combined with previous research related to charging stations and the actual situation in Nanjing [38], this paper sets the values of other parameters as shown in Table 5.

Table 5
Other parameter values.

Parameters	Explanation	Set values
p_f	Fast charger power	60 kW
v	Average travel speed	30 km/h
r_0	Discount rate	0.08
k	Operating years	20 years
η	Conversion factor for operating expenses	0.1
P_c	Battery capacity	42 kW h
D	Maximum mileage	300 km
α	Shape parameter	1.15
c	Scale parameter	195.79
A	Distribution system cost	1.9 million CNY
B	Charging system cost	0.35 million CNY
C	Monitoring system cost	0.2 million CNY
β	Charging range parameter	60%

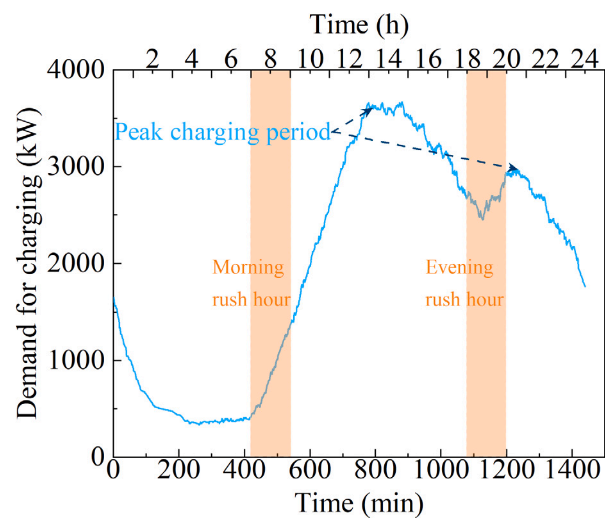

Fig. 8. Charging demand at public charging stations in 24 h.

4.2. EV charging load prediction

According to the nodes of the road network, the following results are obtained by the simulation of user travel behavior based on the trip chain as well as the charging demand simulation prediction, as shown in Fig. 8, which is the one-day charging demand of the charging station in the region. This paper studies public charging posts, so it does not consider the fact that users will charge at private charging posts during their night off. Therefore, from Fig. 8 it can be seen that charging demand gradually decreases from the early hours of the morning, and the bottom of the day's peak charging demand occurs during this time, followed by the morning peak from 7:00–9:00 a.m., where the first peak charging period of the day occurs after the morning peak. Similarly, during 18:00–20:00 is the evening peak, the charging demand is also reduced, and when the charging demand increases again at the end of this period, this simulation prediction is more in line with the users' behavior that most of them are accustomed to choosing fast chargers for charging at the end of the travel peak period [39]. It also shows that this method can achieve more realistic results for user charging demand simulation.

To make the charging demand load distribution in the region more intuitive, this paper combines the charging data obtained from MC simulation to visualize the charging demand load distribution. As shown in Fig. 9, the simulation prediction results of the charging demand load distribution over time at the 47 road nodes show the variation

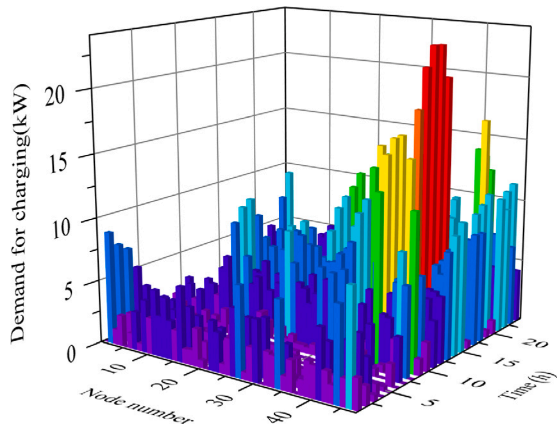

Fig. 9. Nodal charging load demand.

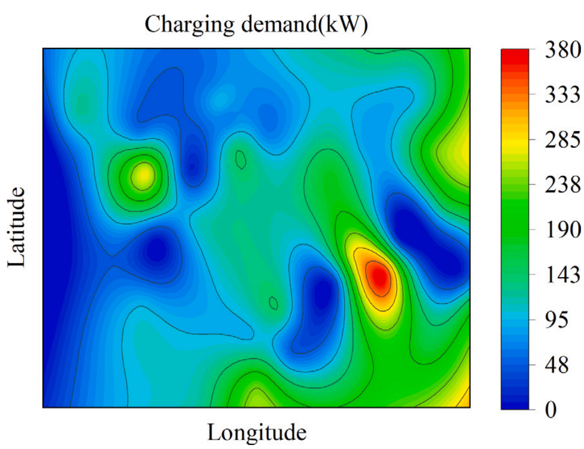

Fig. 10. Space distribution of charging loads.

of the charging load at each road node over a 24-h period. As shown in Fig. 10, the overall spatial distribution of loads obtained by accumulating the 24-h charging loads at each node in the region. It can be seen that the charging demand is higher in areas with dense road network, and on the contrary the charging demand is lower in areas with sparse road network, but this does not mean that the charging station siting in this paper results in the nodes with the highest charging load demand. Building a station in this way will only lead to a larger traffic flow in the area, which in turn will cause traffic congestion, so when solving the siting model, this method considers a variety of factors.

4.3. Single-objective planning

Based on the relevant data obtained from the above charging demand simulation predictions, and considering the related constraints mentioned earlier, we constructed two single-objective siting planning models: Model 1 aims to minimize investment costs, while Model 2 focuses on maximizing user satisfaction. The WOA and PSO were employed to solve the charging station siting layout for each model. As shown in Table 6, it is the result of site selection considering investor's cost and user's convenience respectively, Tables 7 and 8 show the number of charging piles installed in each charging station after planning.

Comparing the planning results obtained from three different solution methods, the WOA produces the most favorable outcomes for investors or users in both site selection models. From the planning results, it can be observed that in areas with higher charging demand, the number of charging piles installed at each station are greater.

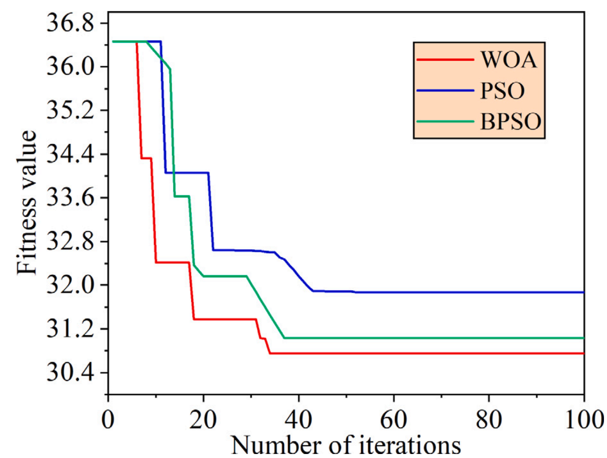

Fig. 11. Convergence curve (Model 1).

Additionally, the station density in these areas tends to be relatively higher.

Comparing the two planning results, when standing from the perspective of the investor and considering only the minimization of the investment cost, the number of stations built is much smaller than the number of stations built when considering only the satisfaction of the users, which keeps the cost at a lower level. However, this station building program makes the search time and the waiting time of users in the queue are relatively long, which brings great inconvenience to the users' charging. When standing from the perspective of the user, only considering the maximization of user satisfaction, it can be seen that the number of stations built has been improved, and the user's time spent searching for stations and waiting in line has been greatly reduced. However, the investment cost of the investor amounted to 41.578 million CNY, which put great pressure on the investor. Meanwhile, the excessive size of charging stations also means that the number of EVs that can be connected to the distribution grid at the same time will rise, which will also bring challenges to the stable operation of the distribution grid. Such result is not reasonable for investors and users, and it is difficult to strike a balance between the two, which can only have a negative effect on the development and popularization of EVs. If users no longer choose EVs for travel, society's dependence on fossil fuels will increase, which is clearly not a reasonable planning result.

In addition, comparing the results obtained by WOA and PSO, Model 1 is planned from the investor's perspective, and the results show that WOA saves 3.51% in costs compared to PSO. Model 2 is planned from the user's perspective, and the results indicate that WOA improves user satisfaction by 5.73% compared to PSO. From the iterative convergence curves in Figs. 11 and 12, it can be seen that PSO is more prone to falling into local optima in the early stages compared to WOA and has a slower optimization speed. To further validate the performance of the method proposed in this paper, Binary Particle Swarm Optimization (BPSO) was also used to solve the two models mentioned above. The results are shown in Table 6. Compared to the planning results of traditional PSO, BPSO demonstrates a significant optimization effect for both models. However, when compared to the results obtained by WOA, WOA saves 0.91% of the cost in Model 1 and increases user satisfaction by 1.2% in Model 2. As shown in the iteration convergence curves in Figs. 11 and 12, BPSO shows a noticeable improvement in optimization performance over PSO, yet still slightly lags behind WOA in the site selection process. In conclusion, WOA outperforms both PSO and BPSO in solving the electric vehicle charging station location problem.

Table 6
Single-objective planning results.

Parameters	Model 1 (WOA)	Model 1 (PSO)	Model 1 (BPSO)	Model 2 (WOA)	Model 2 (PSO)	Model 2 (BPSO)
Number of charging stations	8	9	9	14	13	13
Investment cost (million CNY/year)	30.746	31.865	31.029	41.578	40.291	41.037
Average Station-seeking time (minutes)	54.9	52.6	53.8	23.1	25.1	23.9
Average queuing time (minutes)	63.7	61.5	63.1	19.6	20.1	19.3

Table 7
Model 1 Planning the number of charging piles.

Node (WOA)	Number of charging Piles (WOA)	Node (PSO)	Number of charging Piles (PSO)	Node (BPSO)	Number of charging Piles (BPSO)
7	6	1	3	6	5
10	4	4	5	10	7
18	7	10	2	14	7
22	5	16	7	15	2
28	7	19	4	25	4
32	3	28	8	30	5
38	5	31	3	35	8
42	4	44	7	39	3
/	/	46	6	43	2

Table 8
Model 2 Planning the number of charging piles.

Node (WOA)	Number of charging Piles (WOA)	Node (PSO)	Number of charging Piles (PSO)	Node (BPSO)	Number of charging Piles (BPSO)
7	5	2	3	6	5
9	4	6	5	12	2
10	4	8	3	14	6
13	5	11	2	19	3
16	6	13	6	23	4
19	3	16	3	25	3
21	4	19	4	26	5
24	3	27	2	28	5
26	4	31	3	29	3
27	3	35	6	38	6
30	4	37	4	40	4
32	5	40	5	42	3
38	3	45	4	45	5
42	4	/	/	/	/

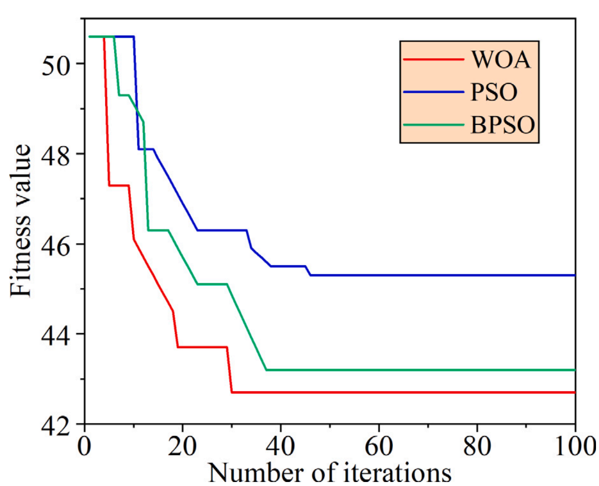

Fig. 12. Convergence curve (Model 2).

4.4. Multi-objective planning

As shown in Table 9, it is the result of using NSWOA to consider the two objective functions at the same time, i.e., the planning scenarios derived from both the investor's and the user's perspectives. From the data in the Table 9, it can be seen that the program obtained when considering multiple objectives for site selection reduces the investor's cost from 41.578 million CNY to 37.742 million CNY, which is a reduction of 9.22%, compared with the program obtained by considering only the objective function 2. In addition, compared to when only objective function 1 is considered, the multi-objective siting scheme results in a significant reduction in both user average station-seeking time and average charging queuing time from 54.9 and 63.7 to 28.6 and 21.7, which is a reduction of 47.91% and 65.83% respectively. Under this planning scenario, the number of charging piles to be installed at each site is shown in Table 10, and the location of each charging station to be built is shown in Fig. 13, where the special color markers are the alternative nodes to be built in the area. The multi-objective site selection method integrates the needs of the investor and the user, reduces the investment cost while at the same time improves the user's satisfaction, so that the EV user's "mileage anxiety" is alleviated in the process of searching for charging stations. At the same time, the reduction of the user's station-seeking time also means that the search distance becomes shorter, which also makes the waste of energy in the search process has also been reduced, with the current increase in the number of EVs, in the huge EV base, will save a lot of energy.

From Table 9, it can also be seen that in the final planning results obtained from solving the multi-objective model, NSWOA saves 2.54% of the investment cost compared to MOPSO. The station search time and the charging queue time for users are also better in the NSWOA results than those of MOPSO. NSWOA improves user satisfaction by 2.52% compared to MOPSO. Moreover, from the Pareto front obtained in the experiment, as shown in Fig. 14, NSWOA demonstrates better optimization performance in the location model solution, with higher

Table 9
Multi-objective planning results.

Parameters	Planning results (NSWOA)	Planning results (MOPSO)
Parameters	11	12
Investment cost (million CNY/year)	37.742	38.725
Average Station-seeking time (minutes)	28.6	29.2
Average queuing time (minutes)	21.7	22.4

Table 10
Multi-objective planning of the number of charging piles.

Node (NSWOA)	Number of charging piles (NSWOA)	Node (MOPSO)	Number of charging piles (MOPSO)
3	4	2	3
5	3	7	5
9	6	9	4
11	4	12	2
18	5	14	6
21	3	15	5
23	7	25	3
32	5	28	7
42	4	30	4
44	3	33	2
47	3	38	4
/	/	39	5

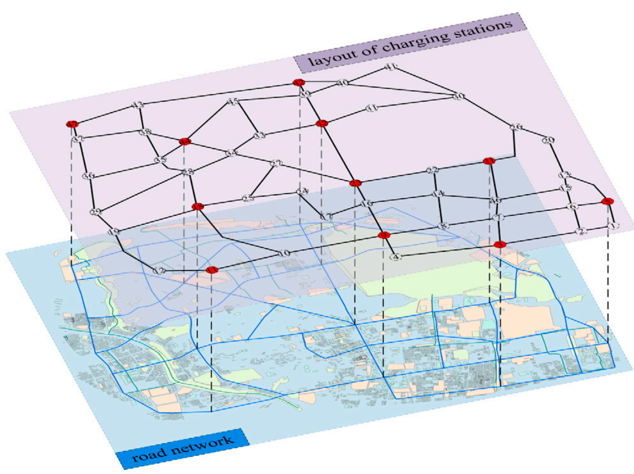

Fig. 13. Results of multi-objective site selection.

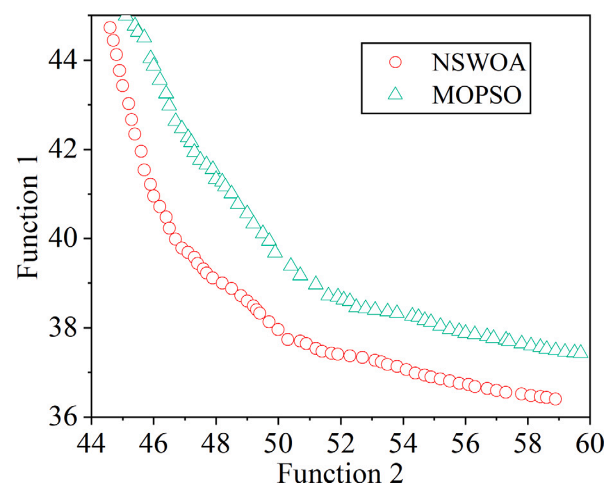

Fig. 14. Pareto Front Diagram.

optimization accuracy than MOPSO, as its solution set consistently occupies a more advantageous position in Fig. 14. In addition, comparing the results of the multi-objective model solved by MOPSO with those of the single-objective model solved by PSO, it can be concluded that in multi-objective planning, the investment cost is reduced by 3.89% compared to single-objective planning, which only considers user satisfaction. The user station search time and charging queue time were significantly reduced, from 52.6 and 61.5 to 29.2 and 22.4, a reduction of 44.49% and 63.57%, respectively. This also shows that the results of the multi-objective planning model, whether solved by NSWOA or MOPSO, are more reasonable than those of the single-objective planning model.

In summary, the simulation and prediction results of electric vehicle travel and user charging behavior, based on the travel chain theory and Monte Carlo method, closely resemble actual situation. Using the simulated travel data obtained from electric vehicle travel and the charging data derived from user charging behavior as a foundation, and considering other relevant constraints, a complex site selection model was constructed. The WOA and NSWOA were employed to solve the site selection problem. Solutions for both single-objective and multi-objective site selection were obtained, and by comparison, it was concluded that the multi-objective scheme better accommodates the needs of both investors and users. Additionally, comparative experiments between WOA and PSO, as well as NSWOA and MOPSO, were conducted, ultimately verifying the feasibility of the proposed method. This has a positive impact on the future promotion of electric vehicles, and in the long term, it can help reduce society's reliance on fossil fuels, contribute to lower carbon emissions, and support the goal of "carbon-neutral".

5. Conclusion

Due to the unpredictable charging needs of EV users and the imbalance between investor costs and user satisfaction in the development of EVs, it has become one of the impediments to the popularization of EV development. So, this paper establishes an EV charging load demand forecasting model based on the trip chain theory and MC method, and constructs EV charging station siting model to solve the regional siting problem with the data obtained in this process, and the conclusions of this paper are as follows:

(1) Based on the concept of EV trip chain, the travel of EVs is described by analyzing the key characteristic quantities such as trip chain length, daily first travel moment, single travel

distance, travel destination type, length of stay, spatial transfer probability, etc., use the MC to simulate the EV's dynamic travel process and the user's charging behavior, the results obtained are more in line with the actual situation.

(2) Analysis of the solution results of the single-objective siting model and the multi-objective siting model constructed in this paper concludes that the multi-objective siting model reduces the cost of the investor and also improves the charging experience of the user, indicating that the siting model is able to balance the interests of the service provider and the consumer, thus promotes the popularization and development of the EV.

(3) Aiming at the traditional WOA cannot solve the multi-objective problem, a process of sorting populations according to on-dominated sorting is introduced to it, so that it can solve the multi-objective siting model constructed in this paper, and the feasibility of the research method in this paper is further verified through the final results.

With the continuous development of EV technology, this paper makes the following outlook for future research: (1) the number of EVs is still increasing, and further research is needed for the planning of supporting charging facilities; (2) the impact brought by numerous EVs connecting to the distribution network can be reduced by the charging behavior of the orderly scheduling guidance.

CRediT authorship contribution statement

Minan Tang: Writing – review & editing, Funding acquisition, Data curation. **Yude Jiang:** Writing – original draft, Software. **Shuyou Yu:** Software, Conceptualization. **Jiandong Qiu:** Investigation, Data curation. **Hanting Li:** Methodology, Formal analysis. **Wenxin Sheng:** Visualization, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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