Research on Location And Capacity of Electric Vehicle Charging Pile Based on CAHA

Qingyun Yuan, YaoHui Zhang, Dongming Zhao, Zishen Wang, Liu Tan

Abstract—**When optimizing the location selection and capacity configuration of electric vehicle charging stations, in order to effectively balance user demand and minimize total construction and operation costs, a location and capacity optimization model for electric vehicle charging stations is constructed with the goal of minimizing the sum of construction cost, maintenance cost, and network loss cost. The model is constrained by charging demand, power flow, branch apparent power, and node voltage to ensure the rationality of charging station layout and the stability of power grid operation. Meanwhile, a chaotic non-uniform mutation artificial hummingbird algorithm (CAHA) is proposed to solve the optimization model and improve its performance. Finally, the verification on the test function shows the superiority of the CAHA algorithm, and when it is used to solve the optimization problem of charging station location and capacity, it can obtain better location and capacity configuration scheme, thereby reducing overall costs.**

Index Terms—**Electric vehicle charging station, chaos non-uniform variation, artificial hummingbird algorithm, location selection and capacity configuration.**

I. INTRODUCTION

WITH The popularity of electric vehicles, the demand for charging is also increasing. As an important supporting facility for electric vehicles, the location and capacity of charging stations directly affect the charging experience and efficiency of electric vehicle users. Through scientific and reasonable location and capacity planning of charging stations, the resource allocation of charging stations can be optimized, the charging efficiency and service quality can be improved, and the construction and operation costs can be reduced, thus promoting the rapid development of the electric vehicle industry. Foreign researchers have carried out a lot of research. on the location and capacity of electric vehicle charging stations. The conventional methods include linear programming, queuing theory, simulation and GIS spatial analysis. For example, Upchurch et al. propose a capacity-constrained river closure model to study the location of electric vehicle charging stations, and validate the effectiveness of the method using a specific case [1]. This method introduces the capacity limit, which can better deal with the complex relationship between the number of serviceable vehicles at the charging station and the actual demand, and provide some ideas for subsequent research. Bayram analyzed the charging load problem of electric vehicles, studied the impact of different charging loads on the power grid, and constructed a constant capacity model of electric vehicle charging piles related to the architecture and charging station network to achieve the most reasonable power distribution [2]. Based on the actual data and considering multiple characteristic quantities, Namdeo and Jung constructed a multi-stage hierarchical analysis model to solve the location problem of electric vehicle charging facilities [3]-[4]. Taking into account the environmental factors, population density, and traffic flow, the optimal location of electric vehicle charging facilities should be preferred when dealing with high traffic flow, high population density, and well-developed infrastructure. In order to improve the efficiency of charging station layout and planning, traditional solution algorithms have been improved. For example, Professor Li added the construction cost of electric vehicle public charging station and the travel cost of users to construct a location model for electric vehicle charging station. The improved genetic algorithm is used to solve the model, which can better search for the global optimal solution, avoid falling into local optimum, and improve the overall performance of the model [6].

Domestic research on the location and capacity of electric vehicle charging stations mostly focuses on modeling, prediction, and optimization algorithms. For example, Su Peng uses an electric vehicle growth prediction model to predict the number of electric vehicles, and then studied the location and capacity planning of electric vehicle charging stations [7]. The research results provide economic analysis for the construction planning of charging stations, helping decision makers achieve optimal configuration under limited resources and maximize the efficiency of charging facilities. In order to comprehensively consider the actual user demand and potential cost fluctuations, Huang Mengchao analyzes the uncertainty of user demand, transforms the original uncertainty problem into a deterministic problem, and finds the optimal solution under the worst case [8]. In addition, Liu et al. combines node demand, transit demand and service radius to construct a location model of electric vehicle charging facilities [9]. Pan Long constructs a charging facility planning model with the highest user satisfaction as the objective function to analyze the user choice behavior [10]. Based on the charging intentions of

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electric vehicle users, Ma Weixing et al. establish a dual-objective optimization scheduling model for charging and discharging of electric vehicles to reduce charging costs and ensure the state of charge (SOC) [11]. Hou Yan-e et al. establish a mixed integer linear programming model, which takes into account the variation of vehicle energy consumption with load [12]. Under the premise of limited capacity of electric vehicle charging station, Hu Dandan et al. study the planning problem of electric vehicle charging facilities under the condition of random charging time and traffic flow, and solve the problem using greedy algorithm and dogleg path trust region method [13]. In addition, Xu Zuqin analyzes the related factors affecting the charging load and uses Monte Carlo simulation method to simulate the charging load of the vehicle. This method can ensure the rationality of charging station planning [14]. However, in order to improve the efficiency of solving the location and capacity model, it is necessary to study solving algorithms. For example, Zhang Juan et al. propose an optimization algorithm that combines fuzzy hierarchy and immune genetic algorithm when studying the layout of electric vehicle charging stations[15]. The results show that the combination algorithm can quickly find the optimal charging station location. Zhang Pengwei et al. construct an electric vehicle path optimization model based on multiple distribution centers and solve it by the scatter search algorithm. The results show that the algorithm has certain advantages in efficiency and accuracy [16]. In addition to these optimization algorithms, the artificial bee-bird algorithm, as an emerging optimization algorithm, has also received extensive attention and research from the academic community. For example, Li Zhen proposes a multi-strategy improved artificial bee-bird algorithm (IAHA) to enhance the search efficiency and solution quality of the algorithm [17]. In addition, Liu Qikai proposed a new artificial bee-bird algorithm for solving discrete optimization problems [18]. The algorithm has been applied to the flow shop scheduling problem, and the results show that it has faster convergence speed and higher accuracy. It can be seen that the advantages of artificial bee-bird algorithm in practical application provide some ideas for its application in the research of electric vehicle charging pile location and capacity.

In summary, most of the current research on the location and sizing of electric vehicle charging stations is to construct the corresponding optimization model, and then solve the model through optimization algorithm. However, due to the numerous factors affecting the location and capacity of charging stations. If these factors are not fully considered, the rationality of the location and capacity model will be greatly reduced. In addition, the algorithm performance of solving the model will also affect the efficiency of the entire location selection and capacity strategy. Therefore, based on the comprehensive analysis of multiple factors that affect the location and capacity of charging stations, in order to simplify the calculation and analysis, the location and capacity model is constructed under certain assumptions. Considering the advantages of artificial hummingbird algorithm in solving complex optimization problems, a chaotic non-uniform mutation artificial hummingbird algorithm is proposed by introducing chaotic mechanism and using non-uniform search strategy to improve the artificial hummingbird algorithm. The algorithm is used to solve the location and capacity model of charging stations, thereby achieving effective configuration of charging stations with minimal cost.

II. Establishment of Optimization Model for Location and Capacity of Electric Vehicle Charging Pile

The location and capacity of electric vehicle charging stations involves many influencing factors, which collectively determine the construction location, scale and service scope of charging stations. Therefore, this section first analyzes these influencing factors and then provides the corresponding location and capacity model of charging station.

A. Analysis of Influencing Factors of Location Selection And Capacity

The main factors influencing the location selection and capacity of electric vehicle charging station are as follows:

(1) In order to meet the charging needs of users, it is necessary to conduct in-depth analysis of the number and growth trend of target user groups and electric vehicles.

(2) Economic factors also play an important role in the location selection of charging stations, involving return on investment, land costs, electricity, and operating costs.

(3) The importance of grid factors is reflected in the integration of power supply capacity, smart grid technology, and renewable energy to ensure the normal operation of charging piles and reduce their burden on the power grid.

The above analysis of the influencing factors not only provides the necessary input data and constraints for model establishment, but also provides a basis for constraints and objective functions, enabling the established model to effectively reflect the actual situation and lay a solid foundation for the location selection and capacity determination of charging stations. The following will elaborate on how to use these factors to construct a charging station location and capacity model.

B. Construction of Location Selection And Capacity Model

The main purpose of selecting the location and capacity of electric vehicle charging stations is to optimize their location and capacity for minimizing the cost. Therefore, this paper proposes a method combining model and optimization algorithm to calculate the optimal number and location of charging stations, in order to achieve the goal of minimizing total cost. Due to the many factors that affect the location and capacity model of charging stations, in order to facilitate the analysis and calculation, when constructing the model, the assumptions are given as follows:

(1) The user 's charging demand is evenly distributed in space, which means that the user 's charging demand is distributed in different regions, rather than concentrated in a specific location.

(2) The geographic information data used is accurate, including maps and road network information, to calculate the coverage area of charging stations and the distance traveled by users.

(3) The capacity of the charging station can meet the

user's charging needs. The user's driving and charging behavior is relatively stable and not affected by external factors. The network connection is also stable and reliable, which ensures that the communication between charging stations is not disturbed by external factors.

(4) Accurate charging demand enables accurate prediction of charging demand.

Based on the above assumptions, the objective function for the location and capacity problem is first given, followed by the corresponding constraints.

C. Objective Function

When selecting the charging station location scheme, in order to maximize the economic benefits, on the basis of considering the construction and operation cost, the maintenance cost and the network loss cost, the minimum sum of these three costs is taken as the objective function.

(1) Construction and operation cost of charging station

The construction and operation cost of charging station include land leasing, infrastructure construction, procurement and installation of charging pile equipment, power access cost, construction cost, operation and management cost, monitoring safety equipment cost and other costs. By minimizing the construction cost, a more cost-effective location scheme can be selected to maximize the benefits within a limited budget. The construction and operation cost W_1 can be expressed as follows:

$$W_1=\frac{(1+r_0)^{n_{year}} r_0}{(1+r_0)^{n_{year}}-1}(C_g+\varphi n_{char}^2+\varepsilon n_{char})+\sum_{i=1}^{I}(C_{coni}+C_{opi}) \quad (1)$$

where r_0 is the discount rate , n_{year} is the number of operating years ,C_g is the fixed investment cost ,n_{char} is the number of charging piles in the charging station , I is the sum of charging stations , φ is the coefficient of cost equivalent investment of distribution transformer and transmission line related equipment , ε is the unit price of charging pile ,$\sum_{i=1}^{I}(C_{coni}+C_{opi})$ is the operating cost.

(2) Maintenance cost of charging station

The maintenance cost of charging station refers to the cost of maintenance, upkeep, and operation of charging station, including the maintenance cost of charging equipment, power consumption cost, personnel management cost, monitoring system maintenance cost, insurance cost and so on. The maintenance cost W_2 of a charging station is usually affected by geographical location and equipment quality, which can be expressed as follows:

$$W_2=(C_g+\varphi n_{char}^2+\varepsilon n_{char})$$

$$\gamma+365\beta\sum_{i=1}^{I}T_{qi}\sum_{j=1}^{N_{um}}pn_j+365\beta\frac{\sum_{i=1}^{I}\sum_{j=1}^{N_{um}}pn_j\lambda_{ij}d_{ij}}{v}$$

$$T_{qi}=\frac{N_{ch}\rho^{N_{ch}+1}P_z}{\lambda N_{ch}(N_{ch}-\rho)^2}$$

$$P_z=\left[\sum_{k=0}^{N_{ch}-1}\frac{\rho^k}{k}+\frac{N_{ch}\rho^{N_{ch}}}{N_{chi}(N_{ch}-\rho)}\right]^{-1} \quad (2)$$

where γ is the conversion coefficient of labor and equipment operation and maintenance cost , N_{um} is the number of charging demand points within the service range of charging station i ,the spatial distance from d_{ij} charging demand point to charging station ,q_j is the average number of electric vehicles that need to be charged every day at the charging demand point ,p is the charging price ,k is the value of user travel time ,v is the average speed of electric vehicles ,β is the urban travel time cost coefficient ,T_{qi} is the waiting time expectation of the electric vehicle queuing ,N_{ch} is the number of charging piles for a site ,$\rho=\frac{\lambda}{\mu N_{ch}}$ is the charging service intensity , $\lambda=\frac{n_{ev}p}{t_c}$ is the number of electric vehicles arriving at the charging station per unit time ,the number of electric vehicles at the n_{ev} demand point , p is the charging probability of electric vehicle ,t_c is the charging period of electric vehicles ,$\mu=\frac{1}{t_s}$ is the average service rate of the charging pile , t_s is the service time of the charging pile, and P_z is the probability that the charging pile is all idle.

(3) Network loss cost

Network loss cost is an important consideration in the study of location selection and capacity of electric vehicle charging stations. The network loss cost W_3 is usually related to factors such as low voltage cost and electricity price, which can be expressed as follows:

$$W_3=p\sum_{i=1}^{N}\sum_{j=\emptyset_i}(real(\frac{1}{Y_{ij}})\cdot\frac{P_{ij}^2+Q_{ij}^2}{U_{ij}^2})+\mu\sum_{i=1}^{N}(\frac{U_i-U_r}{U_{i,max}-U_{i,min}})^2 \quad (3)$$

where N is the total number of nodes, Y_{ij} is branch admittance, Q_{ij}, P_{ij} *is* the active and reactive power flowing from the head end of the branch are respectively,U_{ij} is the head-end voltage of the branch, $\emptyset_i$ is a set of nodes connecting nodes, $real()$is the real part,p for the unit price of charging. $U_i, U_{i,min}, U_{i,max}$ and U_r represent the voltage amplitude, voltage upper and lower limits and rated voltage of the node, respectively, and μ represents the cost of unit voltage offset.

The objective function is to minimize the sum of charging station construction cost, charging pile maintenance cost, and user's driving cost from demand point to charging station. Therefore, the objective function can be expressed as follows:

$$MinF=min[W_1+W_2+W_3] \quad (4)$$

D. Constraint

When selecting the charging station location scheme, it is necessary to consider constraints such as power flow, branch apparent power, node voltage, number of charging piles in the station, and number of charging stations to ensure the rationality and feasibility of the location selection plan. These constraints are described as follows:

(1) Power flow constraints

The power flow constraint ensures that the layout and scale of charging stations can meet the charging demand of electric vehicles without negatively affecting the normal operation of the power grid. Therefore, the relationships must be satisfied as follows:

$$P_{Gh}-P_{Ch}-V_h\sum_{j=1}^{N}V_k(G_{hk}\cos\theta_{hk}+B_{hk}\sin\theta_{hk})=0$$

$$Q_{Gh}-Q_{Ch}-V_h\sum_{j=1}^{N}V_k(G_{hk}\cos\theta_{hk}+B_{hk}\sin\theta_{hk})=0$$
$$(\forall hk\in L,\forall H\in[1,N]) \tag{5}$$

where B_{hk} is the branch susceptance, P_{Gh} and P_{Ch} are the active power of the power generation and charging station load of the power grid node, respectively. Q_{Gh} and Q_{Ch} are the reactive power of the power generation and charging station load of the power grid node, respectively.

(2) Branch apparent power constraint

By designing the apparent power of the branch reasonably, a good interaction between the charging station and the power grid can be achieved. Therefore, the conditions need to be met as follows:

$$S_{hk}=\sqrt{P_{hk}^2+Q_{hk}^2}$$
$$|S_{hk}|\le S_{hk}^{max},\forall hk\in L,\forall h\in[1,N] \tag{6}$$

where S_{hk}^{max} is the maximum apparent power of the branch hk, P_{hk} is the active power in the branch hk, and Q_{hk} is the reactive power of the branch hk.

(3) Node voltage constraints

Considering the node voltage constraint can ensure the stability of the power grid, improve the power quality and investment efficiency, enhance the charging efficiency, and optimize the allocation of power grid resources. Therefore, the conditions need to be met as follows:

$$V_h^{min}\le V_h\le V_h^{max},\forall h\in[1,N] \tag{7}$$

where V_h^{min} is the lower limit of the node voltage, and V_h^{max} is the upper limit of the node voltage.

(4) Constraints on the number of charging piles in the station

In the study of the location and capacity of electric vehicle charging stations, considering the number of charging stations can ensure the efficiency, economy, and user satisfaction of charging services. Therefore, the conditions need to be met as follows:

$$n_{char,min}\le n_{char}\le n_{char,max} \tag{8}$$

where $n_{char,min}$ and $n_{char,max}$ are the maximum number and the minimum number of charging piles in the station, respectively.

(5) The number constraint of charging stations

The number of charging stations can effectively match demand, control costs, optimize space, balance loads, improve service quality, ensure compliance with policy requirements and reduce environmental impacts, so as to establish an efficient, economical and sustainable charging facility network. Therefore, the following relationships need to be met:

$$N_{CH,min}=\left|\frac{n_{ch}}{\tau\cdot n_{ch,max}}\right|$$
$$N_{CH}\ge N_{CH,min} \tag{9}$$

where n_{ch} is the total number of electric vehicles.

E. Optimization Model

From the above objective function and constraints, the model of EV charging station location and capacity optimization can be obtained as follows:

$$MinF=\min\,[W_1(n_{char}、C_g)+W_2(n_{char}、n_{ev}、N_{ch})+W_3(P_{ij,t}、Q_{ij,t})]$$
$$\text{s.t. : Eqs. (5) - (9)} \tag{10}$$

It can be seen from Equation (10) that $MinF$ is the objective function. Here, and n_{char},n_{ev},, N_{ch},are selected as decision variables. By optimizing and determining these variables, the total cost of the system can be minimized, thereby improving the economic benefits of the charging station.

III.THE SOLUTION OF CHARGING STATION LOCATION AND CAPACITY OPTIMIZATION MODEL

Equation (10) is a complex optimization problem involving multiple variables and constraints. Researchers usually use intelligent optimization algorithms to solve this problem. Artificial hummingbird algorithm is an intelligent optimization algorithm that simulates the foraging behavior of hummingbirds in nature. It combines the flight skills with intelligent foraging strategy of hummingbirds, which can be used to solve the location and capacity problem of electric vehicle charging stations. However, the computational complexity and sensitivity of parameter settings in the conventional artificial bee-bird algorithm affect the efficiency of practical applications. Therefore, by introducing chaos theory and non-uniform mutation strategy into the artificial hummingbird algorithm, a chaotic non-uniform mutation artificial hummingbird algorithm is proposed to enhance the global search ability and convergence performance of the algorithm, and to solve the problem in Equation (10).

A. Chaotic Non-uniform Mutation Artificial Hummingbird Algorithm and Its Verification

The Artificial Hummingbird Algorithm (AHA) is a biologically inspired optimization algorithm designed to simulate the information exchange and cooperative behavior of bees when searching for food. In order to obtain a larger initial population and avoid premature local optima, chaotic initialization and non-uniform mutation strategies are introduced into the traditional Artificial Hummingbird Algorithm, forming a chaotic non-uniform artificial Hummingbird algorithm (CAHA). This improvement makes the CAHA algorithm to more effectively balance the relationship between global search and local search, improving the overall performance of the algorithm. The solving process of this algorithm is shown in Fig 1, which shows the operation and optimization strategies of CAHA algorithm at different stages, further elucidating its potential and advantages in complex optimization problems. Through these improvements, CAHA algorithm can not only provide efficient solutions in a wider range of application scenarios, but also show stronger robustness and flexibility in the face of dynamic environmental changes and complex constraints. This enables the CAHA algorithm to effectively optimize the decision-making process in practical applications such as EV charging station location selection, logistics scheduling, resource allocation, etc., promoting the research and development in related fields.

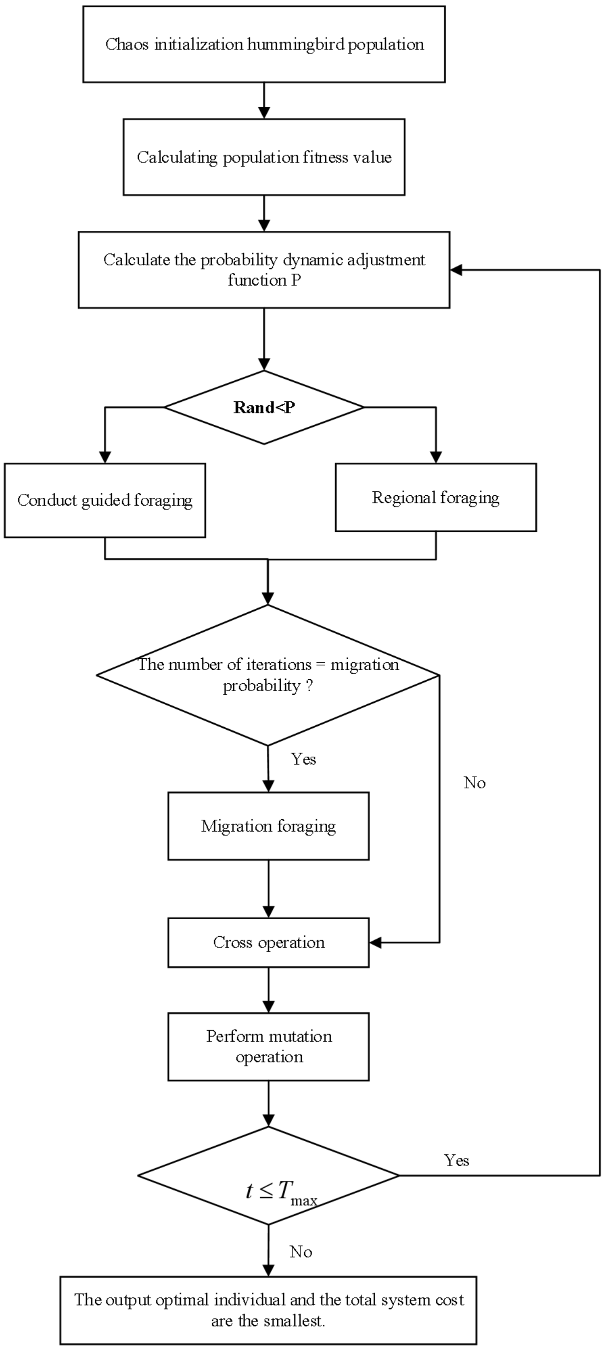


Fig. 1 The solving process of CAHA algorithm

It can be seen from Fig. 1 that the specific solving steps of the algorithm are described as follows:

Step 1: Initialize the parameters of CAHA algorithm, including flight coefficient and migration coefficient, maximum number of iterations and population size.

Step 2: The Tent chaos initialization of Equation (11) is used to strengthen the species diversity of the initial population, and the fitness value of the population is calculated.

$$x_{n+1} = \begin{cases} \frac{x_n}{c} \ , if \ 0 \le x_n \le c \\ \frac{1-x_n}{1-c}, if \ c < x_n \le 1 \end{cases} \tag{11}$$

where c is a control parameter, and x_n is iteratively generated by using the Tent mapping formula to generate a series of values.

Step 3: Conduct guided foraging, territorial foraging, and migratory foraging operations on the initialized population.

Step 4: The hummingbird will give up the current food source and update the food source when the candidate solution generated during the guided foraging or territorial foraging phase is better.

Step 5: The crossover operator is introduced to cross the top one-third of the population's optimal fitness and calculate its fitness.When the fitness of the new individual is better than that of the original individual,replace the original individual to give it a certain probability of escaping rom the local optimal solution.In some cases, crossover operations can be combined to generate new solutions.This operation is usually to determine the crossover of parent individuals by an effective selection mechanism.Assuming that there are two parent solutions $X_1$and X_2,the crossover operation is expressed as follows:

$$X^{'} = \alpha \cdot X_1 + (1-\alpha) \cdot X_2 \tag{12}$$

where α is a random number, the value range is [0,1].

Step 6: The mutation operator is introduced to reduce the disadvantage of population diversity reduction in the later stage of iteration. The mutation step, assuming that there is a solution X and $X^{'}$ after the mutation solution, the mutation can be expressed as follows:

$$X^{'} = X + \mu \cdot (\mathrm{U}-\mathrm{L}) \cdot \mathrm{C} \tag{13}$$

where μ is the mutation rate, which is usually a gradually decreasing value from 1 to 0. U and L are the upper and lower bounds of the search space, respectively. C is a random number that can be generated by chaotic mapping or other random methods to ensure it falls within the range of [0,1].

Step 7: Satisfy the maximum number of iterations, output the result, and the iteration ends.

B. Performance Verification of the Algorithm

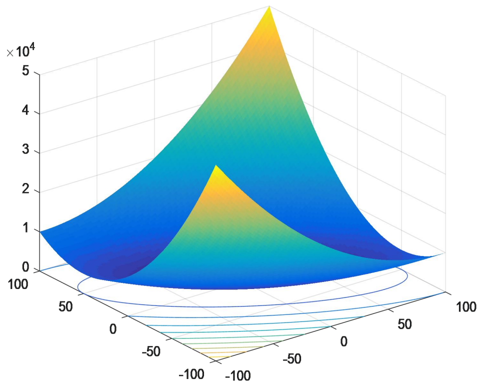
In order to verify the superiority and feasibility of the proposed CAHA algorithm compared with the traditional AHA algorithm and PSO algorithm,four classic CEC23 sets of test functions,Sphere,Ackley,Griwank and Rastrigin,are used for verification.The images of these functions are shown in Fig.2.

The target values of the four test functions of the CEC23 group are 0,the maximum number of iterations of the set function is 100,the population size is 30,and the dimension of the test function is 30.Each function is subjected to 30 independent experiments, and the average value and standard deviation in the experiment are recorded to evaluate the effect of the algorithm.Additional information about the test function is shown in Table 1.

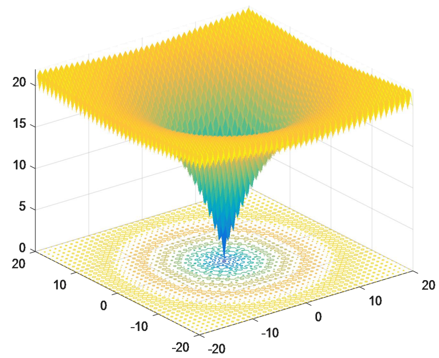
TABLE I

INFORMATION TABLE OF TEST FUNCTIONS

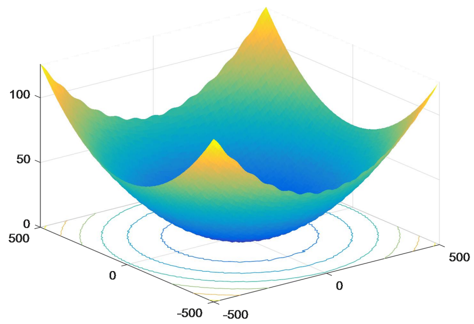
Function type	Test function	Search range	Optimum
Sphere	$f(x) = \sum_{i=1}^{n-1} x_i^2$	[-100,100]	0
Ackley	$f(x) =- 20exp(- 0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2})$	[-32,32]	0
Griwank	$f(x) = \sum_{i=1}^{d} \frac{x_i^2}{4000} - \prod_{i=1}^{d} cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600,600]	0
Rastrigin	$f(x) = 10d + \sum_{i=1}^{d} [x_i^2 - 10cos(2\pi x_i)]$	[-5.12,5.12]	0



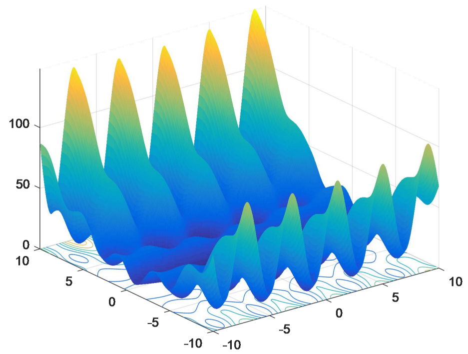
(a) Sphere



(b) Ackley

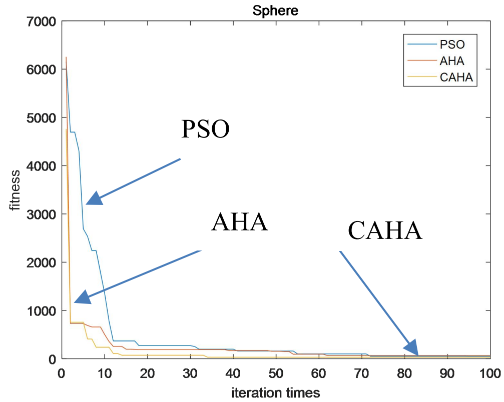


(c) Griwank

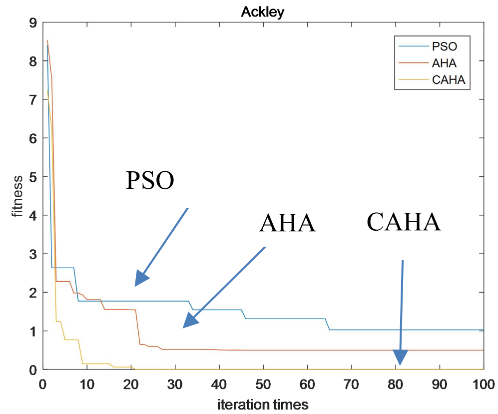


(d) Rastrigin
Fig.2 Test function image

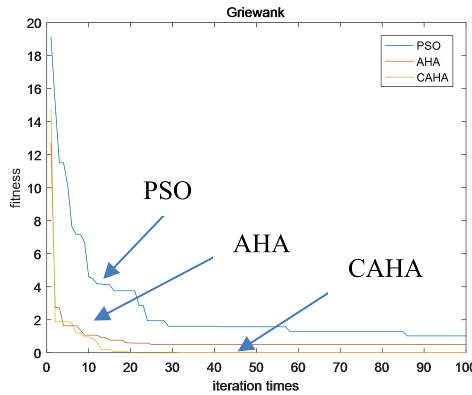
The PSO, AHA and CAHA algorithms are used to iteratively solve the four test functions in Table 2. The curve of fitness value with the number of iterations is shown in Fig. 3.



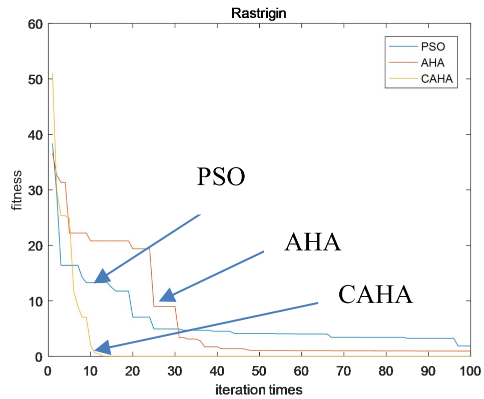
(a)Sphere



(b)Ackley



(c)Griwank



(d)Rastrigin
Fig.3 Comparison of evolutionary iterative curves for solving different test functions

It can be seen from Fig.3 that the CAHA algorithm in the Sphere function can achieve the optimal fitness value by 35 iterations,while the PSO algorithm and AHA algorithm require 65 and 70 iterations respectively to achieve the optimal itness value.In the Ackley function,the CAHA algorithm can achieve the optimal fitness value by 20 iterations,while the PSO algorithm and the AHA algorithm need 27 and 65 iterations respectively to achieve the optimal fitness value,with fitness values of 0.5 and 1.3.In the Griwank function,the CAHA algorithm can achieve the optimal fitness value, with a fitness value of 0 after 15 iterations,while the PSO algorithm and the AHA algorithm need 25 and 85 iterations respectively to achieve the optimal fitness value,with fitness value of0.2 and 1.In the function, the CAHA algorithm can achieve the optimal fitness value, with a fitness value of 0 after 12 iterations,while the PSO algorithm and the AHA algorithm need 46 and 97 iterations respectively to reach the optimal fitness value,with the fitness value of 1 and 2.It can be seen that the CAHA algorithm has the best iterative speed and optimization ability.In order to further quantitatively compare the performance of the algorithm,30 independent optimizations are performed for each algorithm.The average and standard deviation of each algorithm are shown in Table 2.The calculation formulas for the average and standard deviation are as follows:

$$Z = \frac{\sum_{i=1}^{n} x_i}{n} \tag{14}$$

where Z is the average value, n is the number of optimizations, and x_i is the result of the n-th optimization.

$$s = \sqrt{\frac{\sum_{i=1}^{n} (x_i - Z)^2}{n}} \tag{15}$$

where s is the standard deviation.

TABLE II

ERFORMANCE COMPARISON OF TEST FUNCTIONS

function types	PSO		AHA		CAHA	
	Z	s	Z	s	Z	s
Sphere	9.15×10^{-5}	9.40×10^{-5}	1.50×10^{-140}	5.70×10^{-140}	0	0
Ackley	3.20×10^{-1}	5.20×10^{-1}	4.45×10^{-16}	0	4.45×10^{-16}	0
Griwank	7.70×10^{-3}	7.10×10^{-3}	0	0	0	0
Rastrigin	5.65×10	1.65×10	0	0	0	0

It can be seen from Table 2 that in the test of unimodal function Sphere and Griwank, the standard deviation of CAHA algorithm is 0, indicating that the stability and consistency of the algorithm are very high. In this case, the average value of CAHA algorithm is close to the theoretical optimal value, which further verifies its better optimization ability. In the test of multi-peak function Rastrigin and Ackley, the CAHA algorithm also performs well. The average value also reaches the theoretical optimal value, and the standard deviation is 0, indicating that the results of each optimization are consistent, which proves the reliability of the algorithm. This shows that despite facing multiple extreme points, the CAHA algorithm can still effectively optimize and quickly jump out of the local optimal solution. In summary, whether in the optimization of unimodal function or multimodal function, CAHA algorithm shows strong search ability and high stability, and has good adaptability to different types of functions. These characteristics make the CAHA algorithm have wide application potential in optimization problems. Furthermore, it will be used to solve the location and capacity problem of subsequent electric vehicle charging stations.

C. Example Verification

F irstly,the location information of 49 demand points and 32 alternative points is determined,and the charging demand of each demand point and the construction cost of charging station are provided. At the same time,the unknown parameters of the charging station location and capacity optimization model are determined.Then,the artificial hummingbird algorithm of chaotic non-uniform mutation is applied to solve the specific location and capacity model.

This paper designs a small-scale case,the road distribution map of the urban planning area and the distribution network structure map of the planning area are shown in Figs.4-5.

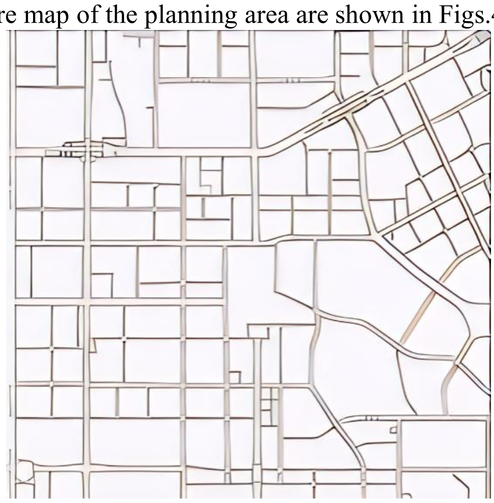


Fig. 4 Geographic map of road distribution in a planning area of a northern city

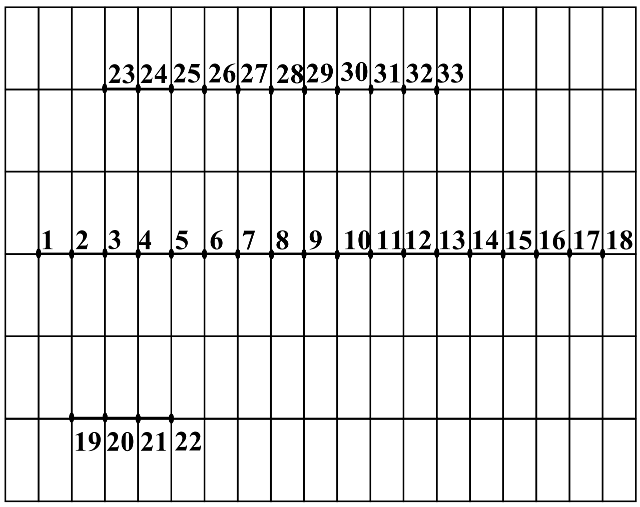


Fig. 5 Distribution network structure diagram in the planning area

Fig. 4 shows the geographical map of road distribution in a planning area of a northern city, the range of its abscissa and ordinate determines the number of demand points in the area is 49.Fig.5 represents 33 key positions in the power grid model,with a replacement point set every other node to determine that the number of alternative points is 32.

TABLE III

INFORMATION OF DEMAND POINTS

Demand point number N_{um}	abscissa (km)	ordinate (km)	Number of electric vehicles n_{ev}
1	0.93	0.74	154
2	1.43	1.90	170
3	1.09	1.95	167
4	4.39	0.84	118
5	0.55	6.87	113
6	6.17	5.59	163
7	5.42	5.87	117
8	6.94	5.20	103
9	3.69	4.13	156
10	4.91	2.61	188
11	6.68	5.29	167
12	4.04	0.94	119
13	2.12	1.18	137
14	7.32	0.16	146
15	0.27	7.71	198
16	2.45	7.76	116
17	7.30	0.99	186
18	2.74	3.74	164
19	2.32	5.25	138
20	0.91	2.32	119
21	6.87	6.04	143
22	1.02	4.46	148
23	2.49	3.42	112
24	6.73	2.14	159
25	3.75	6.03	123
26	4.61	7.19	138
27	4.37	5.83	158
28	5.24	3.25	125
29	0.22	7.51	129
30	3.96	2.04	162
31	0.24	4.27	127
32	6.20	7.64	182
33	2.55	2.14	198
34	6.35	2.00	173
35	1.85	7.42	134
36	4.36	0.55	158
37	7.03	2.40	111
38	0.36	4.73	191
39	0.40	1.63	188
40	0.15	5.09	182
41	5.11	6.39	126
42	4.49	4.01	159
43	0.86	5.21	102
44	5.97	6.37	143
45	4.63	1.87	131
46	0.53	4.81	116
47	0.52	0.90	118
48	1.02	4.13	142
49	5.92	6.70	109

The coordinates of 49 demand points and 32 candidate points are randomly generated by the rand function. The charging demand of each demand point is a random integer generated by the rand function, ranging from 0 to 200. The information of demand points and alternative points randomly generated by rand and pdist2 functions is shown in Table 3 and Table 4.

TABLE IV

INFORMATION OF ALTERNATIVE POINTS

Alternate point number N	abscissa (km)	ordinate (km)	load (MW)
1	6.91	1.10	0.10
2	3.74	4.04	0.09
3	2.08	3.24	0.12
4	4.89	1.39	0.06
5	6.88	4.60	0.06
6	3.82	4.85	0.20
7	7.31	1.72	0.20
8	1.48	4.16	0.06
9	0.83	7.91	0.06
10	2.23	3.92	0.05
11	2.97	5.56	0.06
12	3.16	3.29	0.06
13	2.34	0.28	0.12
14	5.20	2.34	0.06
15	0.69	6.41	0.06
16	3.02	2.77	0.06
17	2.21	0.67	0.09
18	1.75	1.25	0.09
19	0.79	2.93	0.09
20	4.45	5.92	0.09
21	1.00	1.25	0.09
22	1.16	6.44	0.09
23	0.00	6.54	0.42
24	2.13	1.52	0.42
25	4.13	0.99	0.06
26	6.53	6.57	0.06
27	0.32	5.10	0.06
28	6.79	0.13	0.12
29	0.98	7.17	0.20
30	6.25	4.12	0.15
31	6.00	6.00	0.21
32	6.88	2.00	0.06

In addition, other parameters values are shown in Table 5, including discount rate (r_0), operating life (n_{year}), fixed investment cost (C_g), equivalent investment coefficient of distribution transformer and transmission line related equipment cost (φ), unit price of charging pile (ε), conversion coefficient of labor and equipment operation and maintenance cost (γ), charging price (p), average speed of electric vehicle (v), urban travel time cost coefficient (β), charging probability of electric vehicle (P), charging time period of electric vehicle (t_c), and service time of charging pile (t_s).These parameters play a crucial role in the construction and optimization process of the model, which not only affect the calculation of the overall cost, but also directly affect the effectiveness of the location and configuration strategy of the charging station.Through the reasonable setting and optimization of these parameters, it can more accurately reflect the economic situation and user needs in the actual operation, and then provide a scientific basis for the planning and construction of electric vehicle charging infrastructure. As the EV market continues to evolve, it is increasingly important to understand and adjust these parameters to ensure the efficiency and sustainability of the charging network.

TABLE V

VALUES OF OTHER PARAMETERS

Parameters	Character name	Taking values
r_0	Discount rate	0.08
n_{year}	Years of operation	20 years
C_g	Fixed investment cost	300 million ¥
φ	Cost equivalent investment coefficient of distribution transformer and transmission line related equipment	2 million ¥
ε	Charging pile unit price	10 Ten thousand ¥
γ	Labor, equipment operation and maintenance cost conversion coefficient	0.1
p	Charging price	0.8¥/(kw/h)
k	User travel time value	17¥/h
v	The average speed of electric vehicles	20km/h
β	Urban travel time cost coefficient	17¥/h
p	Charging probability of electric vehicle	0.05
t_c	Electric vehicle charging period	4h
t_s	The service time of charging pile	12h

From the above parameters, a specific location and capacity model of electric vehicle charging piles can be obtained for subsequent optimization and solution.

D. Solution Results and Analysis

For the determined location and capacity model,the chaotic non-uniform mutation artificial hummingbird algorithm is used to solve it.To verify the superiority of the algorithm,the particle swarm optimization algorithm and the conventional artificial hummingbird algorithm are used to solve the model.The curve of the total cost changing with the number of iterations is shown in Fig.6.

From Fig.6,it can be seen that the convergence speed and global optimization ability of CAHA are better than PSO and AHA.This is mainly due to the non-uniform mutation of the chaotic non-uniform mutation artificial hummingbird algorithm,which can adjust the mutation range according to the current search phase and improve its adaptability to the problem.By incorporating complex constraints into the objective function,the model scale can be reduced and the solving speed is the fastest.

From the minimum total cost in Fig.6,the corresponding charging station location results of each algorithm can be obtained,as shown in Figs.7-9.

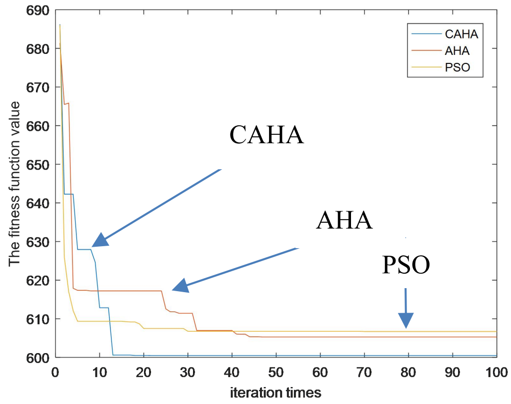


Fig. 6 The change of total cost with the number of iterations

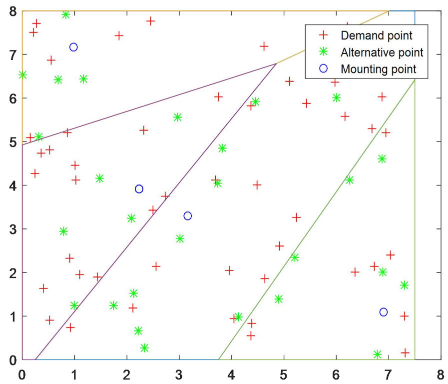


Fig. 7 Charging station location results obtained by PSO algorithm

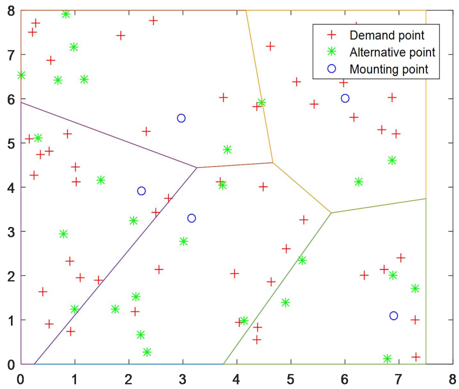


Fig. 8 Charging station location results obtained by AHA algorithm

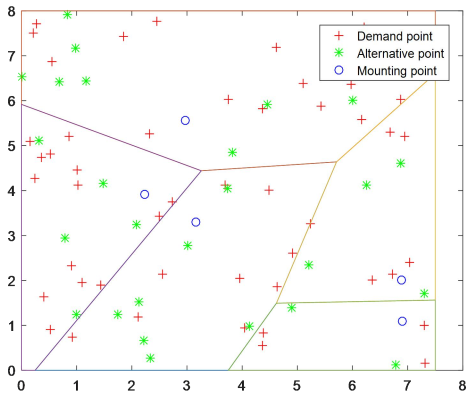


Fig. 9 Charging station location results obtained by CAHA algorithm

In Figs. 7-9, the units of the horizontal and vertical axes are both kilometers, and the area range is determined by the horizontal and vertical coordinates, which facilitates the accurate selection and analysis of the coordinates of the demand points and alternative points. In the figure, the small blue circle represents the installation points of five EV charging stations, which are located in the central area of demand points and alternative points to maximize the charger needs of users. The small red mark represents 49 demand points, which represent the actual charging demand location of electric vehicle users, distributed throughout the region, reflecting the distribution characteristics of users. The small green markers represent 32 alternative points that are potential sites for charging stations, offering flexible options to respond to different needs and conditions. As can be seen from Figs.7-9, the charging station positioning results obtained by the CAHA algorithm show that the distribution of demand points and alternative points around the installation point is more uniform than that obtained by the PSO (particle swarm optimization) algorithm and the AHA (ant colony algorithm) algorithm. This uniform distribution means that charging stations are able to cover user needs more effectively and reduce the average distance of users to charging stations, thereby improving the accessibility and convenience of charging services. Therefore, the positioning result obtained by using CAHA algorithm is considered to be the most reasonable and effective choice. From this, the specific costs corresponding to each algorithm can be found as shown in Table 6.

TABLE VI

COST COMPARISON OF EACH ALGORITHM

Algorithm	L	CAOC / 10,000 ¥	UCTC / 10,000¥	DOC / 10,000¥	CC / 10,000¥
PSO	13,12,30,11,2	183.64	112.90	310.17	606.71
AHA	13,12,32,11,2	182.95	115.21	307.78	605.29
CAHA	13,12,33,11,2	182.87	109.10	308.51	600.48

Where L represents the location, CAOC represents the construction and operation cost,UCTC represents the user charging time cost, DOC represents the distribution operation cost, CC represents the comprehensive cost.

According to Table 6, the comprehensive total cost obtained by CAHA algorithm is the lowest, reaching 60.48 million yuan. This significant cost advantage is mainly due to the innovative design of the chaotic heterogeneous artificial hummingbird algorithm. By introducing chaotic mapping technology, the algorithm enhances the global search ability and reduces the risk of falling into the local optimal solution. In traditional algorithms, the trap of local optimal solution often leads to low search efficiency, but the design of CAHA algorithm effectively avoids this problem. In addition, CAHA algorithm adopts flexible mutation strategy, which can dynamically adjust the search strategy according to the feedback in the search process, so as to achieve a good balance between global search and local search. The flexibility of this strategy enables the algorithm not only to converge quickly, but also to perform well in the quality of the results. Experiments show that CAHA algorithm is superior to PSO algorithm and AHA algorithm in terms of convergence speed and result quality, showing its advantages in solving complex optimization problems. In this specific area, all three algorithms set the locations of 5 charging stations, which indicates that CAHA algorithm can achieve the lowest total cost under this condition. This result not only reflects the effectiveness of the CAHA algorithm in optimizing the location of EV charging stations, but also shows that the strategy can significantly reduce the total cost of the system, thereby improving the overall economic benefits. By optimizing the layout of charging stations, the CAHA algorithm can improve the accessibility and efficiency of charging services, providing EV users with a more convenient charging experience and promoting the widespread use and sustainable development of EV.

IV.CONCLUSION AND PROSPECT

A. Conclusion

This study aims to address the optimization for location and capacity of electric vehicle charging stations. By constructing an efficient optimization model, the total construction and operation costs of charging stations can be minimized to meet the charging needs of users. Firstly, a model is established that minimizes comprehensive cost, including construction cost, maintenance cost and network loss cost. The model involves multiple constraints such as power flow, branch apparent power, and node voltage to ensure the scientific and feasible layout of charging stations. And an improved chaotic non-uniform mutation artificial bee bird algorithm (CAHA) is proposed for solving the model. The comparative experiments results show that the CAHA algorithm performs particularly well in terms of convergence speed and result accuracy, and can achieve the lowest comprehensive cost. Finally, the effectiveness of the proposed algorithm is verified through solving a practical case, and the charging station location scheme and charging resource allocation effect after solution are demonstrated, ensuring the effective implementation of user charging demand.

B. Outlook

Although some progress has been made in the research on the location selection and capacity determination of electric vehicle charging stations, there are still some limitations. In future related research, the following technical methods can be discussed in depth. Multiple objective functions such as environmental impact and user satisfaction can be considered for optimization to achieve more comprehensive decision support, ensuring that environmental protection and social benefits are taken into account while pursuing economic benefits. In addition, the intelligent algorithm needs to be constantly improving to enhance its convergence speed and adaptability in solving complex problems.

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