International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8322-8336

https://doi.org/10.70517/ijhsa463711

Exploration of Charging Station Siting Optimization Method Based on Taboo Search Algorithm

Huanyong Zhang[1] and Guoqing Cheng[1,*]
[1] School of Business, Jiangnan University, Wuxi, Jiangsu, 214122, China
Corresponding authors: (e-mail: c2803568296@163.com).

Abstract With China's rapid economic development, environmental pollution and energy security issues are becoming more and more prominent, and electric vehicles, as a kind of low-pollution, renewable energy-driven transportation, have become an important alternative to traditional fuel vehicles. However, the popularization of electric vehicles faces the problem of insufficient charging infrastructure. Reasonable charging station siting not only reduces the construction cost, but also enhances the user's charging experience. This study proposes an optimization method for electric vehicle charging station siting based on the forbidden search algorithm. By constructing a multi-objective optimization model, factors such as construction cost, user satisfaction, carbon emission and charging station service capability are considered, and the hybrid genetic taboo search (GATS) algorithm is used to solve the problem. The results show that the GATS algorithm exhibits high accuracy and fast convergence speed in the optimization process. In the test of the IEEE 30-node system, the optimized siting scheme using this method reduces the line network loss by about 15% compared to the traditional method, and the construction cost is reduced by about 10%. In addition, the siting scheme considering V2G mode further reduces the grid losses and carbon emissions. Overall, the proposed method can effectively balance the cost, carbon emission and user demand, and provides a feasible optimization scheme for the layout of EV charging infrastructure.

Index Terms forbidden search algorithm, charging station siting, electric vehicle, optimization model, GATS algorithm, carbon emission

I. Introduction

With the rapid development of social economy and the continuous improvement of people's living standard, the number of automobiles in the world is growing explosively, which greatly improves the convenience of travel and quality of life of the residents, but also poses a serious challenge to energy security [1], [2]. In particular, the consumption of large amounts of fossil fuels has not only pushed up the world's energy prices, but also caused the emission of large amounts of greenhouse gases, such as carbon dioxide, which has aggravated global warming and posed a serious challenge to the ecological environment and the sustainable development of human society [3]-[5]. In this context, green new energy vehicles, represented by electric vehicles, have become the mainstream of the development of the automobile industry in countries around the world [6]. Promoting the use of new energy vehicles in cities is one of the most important means to address fossil fuel dependence, reduce greenhouse gas emissions and improve air quality. Electric vehicles have received increasing attention from the energy and power industries due to their low operating and maintenance costs and their ability to significantly reduce carbon emissions [7]. With the rapid increase in the number of electric vehicles, the growing load and the access of electric vehicle charging stations bring great challenges to the stable operation of the distribution network [8], [9]. Among them, the siting of EV charging stations has a significant impact on the power loss, voltage distribution, and harmonic distortion of the distribution network [10], [11]. Therefore, optimizing the siting of charging stations is crucial for maintaining the stable operation of distribution networks.

Many studies have been conducted in the literature on the siting of electric vehicle charging stations. Islam et al [12] used the transportation power loss of electric vehicles, charging station construction cost and substation power loss as an objective function to optimize the siting of electric vehicle charging stations by dichotomous method. Lin et al [13] proposed to construct a charging station siting planning model using gas station network data, geographic information system (GIS) data, population data and regional economic data. Ouyang et al [14] proposed a charging station siting planning model with a two-stage approach with the objective of maximizing the coverage of traffic flow under a limited budget, while considering the partial charging behavior and elastic demand of tram users. Neyestani et al [15] optimized EV siting by considering four metrics as constraints: parking profit, power loss, voltage variation and distribution network stability.

For the algorithmic research on the optimal solution of the site selection of electric vehicle charging stations, many scholars have carried out research from decision-making algorithms, machine learning algorithms, and intelligent optimization algorithms, and have achieved good results [16]. In terms of decision-making algorithms, Sharma et al [17] constructed an EV charging station siting model with land cost, charging time cost and energy cost as the decision-making objectives based on the consideration of road congestion and grid capacity, and solved this siting model using a fuzzy inference algorithm. Liu et al [18] proposed a multi-criteria decision-making method based on gray DEMATEL and ULMULTIMOORA for determining the optimal location of EV charging stations, which was validated through a validation in Shanghai, China, and achieved good benefits. Wu, Y et al [19] combined the PROMETHEE decision algorithm with a cloud model to propose a new approach for EV charging station siting decision making, aiming to address the limitations of the existing approaches by improving the confidence and descriptive certainty of the decision maker. In terms of machine learning, Tungom et al [20] established a neural network-based electric vehicle charging demand prediction model by combining the geographic location information of the charging station sites, and constructed a charging station siting model based on the predicted demand. In terms of intelligent optimization algorithms, the most commonly used is genetic algorithm to solve the optimal siting problem. For example, Hong and Shi [21] proposed a multi-objective optimization model using a multi-objective genetic algorithm (NSGA-II) for solving the challenges faced in the siting of EV charging stations, which takes into account both economic and coverage benefits. Akbari et al [22] investigated the optimal configuration of electric vehicle charging stations by using genetic algorithms to find out the number and optimal location of charging stations that satisfy the customer's needs, taking into account the constraints such as charging power, charging time, and driving distance.

Taboo Genetic Algorithm (TGA) is a hybrid optimization algorithm that combines the global search capability of genetic algorithm with the local optimization property of taboo search [23]. The core idea is to generate diverse candidate solutions through genetic algorithms and utilize a taboo search strategy to avoid repeated searches or falling into local optimal problems [24]. The algorithm has better convergence and robustness compared to genetic algorithm [25]. In solving the charging station siting optimization problem, Wang, B et al [26] constructed a multi-objective optimization model for charging station siting considering user interests and operator costs based on the analysis of the impact of charging station construction on the transportation network, and used an improved forbidden genetic algorithm to solve the siting model. Liu, H et al [27] constructed a charging station siting model for electric vehicles by considering the driver's charging selection behavior as well as the range anxiety problem, and solved it by using the forbidden search algorithm, and verified its effectiveness through empirical analysis. In summary, scholars at home and abroad have achieved remarkable research results on the problem of electric vehicle charging station siting.

Electric vehicles, as clean energy transportation, have become an important measure to promote green mobility around the world. With the increase in the number of electric vehicles, charging stations, as an important part of the electric vehicle infrastructure, and their rational layout are crucial to promote the popularization of electric vehicles. Existing research on charging station siting mostly focuses on considering charging station construction cost and operational efficiency, but with the increase in the number of electric vehicles, pure economic optimization can no longer meet the increasingly complex social needs. Therefore, charging station siting needs to be optimized in terms of construction cost, user satisfaction, carbon emission and other dimensions, to ensure that its reasonable layout can effectively improve the convenience of electric vehicle use and the operational efficiency of the system.

In this paper, by constructing a multi-objective optimization model for electric vehicle charging station siting, the construction cost of charging station, user satisfaction and carbon emission of the system are taken as the optimization objectives, and combined with the characteristics of the taboo search algorithm, a hybrid hereditary taboo search (GATS) algorithm is proposed to solve the problem. The study mainly focuses on how to efficiently search for the optimal solution in the global range by the GATS algorithm, and use the local optimization ability of taboo search to improve the global optimization seeking performance of the algorithm. At the same time, considering the impact of V2G mode on the system, a comparative analysis of optimization for the two modes is proposed, which is used as the basis for formulating the optimal siting scheme, and ultimately provides a feasible solution for the layout of EV charging stations.

II. Modeling

With China's economic development, environmental pollution and energy security issues are becoming increasingly prominent. It has become a trend to seek a green and sustainable transformation of energy in the field of transportation, and electric vehicles are one of the means of transportation powered by renewable and low-pollution electric energy, which has become an important choice to replace traditional fuel vehicles. Reasonable layout and construction of charging infrastructure is an important foundation for popularizing electric vehicles. With the large-scale surge in the number of electric vehicles causing a large number of charging needs, a good and orderly station layout can reduce the charging station construction costs and improve user satisfaction, so it is of great significance to study the optimization of electric vehicle charging station site selection.

II. A. Objective function and constraints

II. A. 1) Objective function

The comprehensive total cost of electric vehicle charging station F includes the charging station construction and operation cost F_1, which mainly includes the cost of land, the cost of new charging piles and the cost of other equipments, the cost of the annual elapsed time en route F_2 and the cost of annual queuing and waiting time of the user F_3, and the cost of environmental protection loss F_4. The objective function is:

$$\min F = \alpha F_1 + \beta (F_2 + F_3) n_{year} + \psi F_4 \tag{1}$$

where n_{year} is the planning period of charging station, set to 6 years, α, β is the coefficient of weighing the user side and the operator side, and different values represent different interests.

(1) Charging station construction and operation cost

This cost can be viewed as a function of the number of chargers, and covers the initial cost of purchasing the land for construction, fire protection, distribution facilities, drainage, chargers, building and road paving, and other investment costs before the end of operation, as well as the annual cost of maintenance and repair of equipment, hiring of professionals, and installation of other accessories after the start of operation. Charger for the charging station is the main body, the larger the scale of the charging station, the more the number of chargers, expressed as follows:

$$F_1 = \sum_{i}^{N} \left[\frac{r_0 (1 + r_0)^m}{(1 + r_0)^m - 1} C(Q_i) + U(Q_i) n_{year} \right] \tag{2}$$

$$C(Q_i) = W + qQ_i + eQ_i^2 \tag{3}$$

$$U(Q_i) = 0.1 \times C(Q_i) \tag{4}$$

where N is the number of charging stations constructed, r_0 is the discount rate, m is the depreciation period, Q_i is the number of chargers in the No. i charging station, $C(Q_i)$ is the construction investment cost function, $U(Q_i)$ is the annual operating cost function of the charging station, which is 15% of the construction cost of the initial investor, and W is the fixed investment.

(2) The annual cost of time consumed by electric vehicles from the charging demand point to the charging station and the cost of queuing waiting time, i.e:

$$F_2 = f_w \times 365 \times \sum_{i}^{N} \sum_{j \in J_{cs_i}} \sum_{k \in E(J_{cs_i})} \frac{\phi d_k}{v} \tag{5}$$

$$F_3 = f_w \times 365 \times \sum_{i}^{N} \sum_{t} W_{i_i} n_{i_i} \tag{6}$$

where J is all the charging demand points, J_{CS_i} is all the charging demand points where the user makes a choice to go to the charging station of i, $k \in E(J_{CS_i})$ is the set of paths that the user passes through to reach the charging station from the charging station of i to the charging station of j, ϕ is the road coefficient, and d_k is the length of road number k. v is the vehicle traveling speed, W_{i_i}, n_{i_i} is the waiting time consumed and the number of cars being charged when the user reaches charging station i, where t is the time period in which it is located.

(3) Environmental loss cost

After a large number of electric vehicles are connected to the regional distribution network, due to the clustering effect, the load will be greatly increased in a certain period of time, changing the distribution of the current of the grid and increasing the loss of the grid, which represents the cost of environmental losses. If the environmental losses of the charging station is not controlled, in the peak load period, the construction of the charging station capacity is too large, the nearby residents have to come here to charge, which will greatly change the local load, resulting in a significant threat, so not only consider the construction costs, charging station capacity is not necessarily a good thing, choose the appropriate diversion of the grid for the benefit of the security of the operation of the grid. Then:

$$F_4 = Cost_p P_{loss}(\delta_i P_{t,i}) \tag{7}$$

where $P_{t,i}$ is the active power of the corresponding node of the charging station, P_{loss} is the network loss, and $Cost_p$ is the discounted cost.

(4) Minimize the additional carbon emissions triggered by the EV users driving to the charging station, i.e:

$$\min F_5 = F_{CO_2} \tag{8}$$

The carbon emissions caused by an electric vehicle with charging demand while driving to a charging station can be expressed as:

$$F_{CO_2} = K_{CO_2} \sum_{i=1}^{I_{cs}} \sum_{j=1}^{Jq} A_i P n_j Z_{ij} d_{ij} \mu_{ij} \tag{9}$$

where J_q is the set of EV charging demand points, P is the single-day fast charging probability of EVs, n_j is the number of EVs at the demand point j, Z_{ij} is the non-straight coefficient of the urban road from the demand point j to the charging station i, and d_{ij} is the spatial straight-line distance from the demand point j to the charging station i. μ_{ij} is the degree of road congestion from the demand point j to the charging station i, which is related to the population density and traffic flow, and mainly affects the average elapsed time to reach the destination.

For the calculation of K_{CO_2}, the specific formula is:

$$K_{CO_2} = k_e \times \frac{E_{100km}}{\eta_e \times 100 \times (1-\theta)} \tag{10}$$

$$k_e = \sum_{g \in G} (EF_g \times \frac{EQ_g}{\sum_{g \in G} EQ_g}) \tag{11}$$

where K_{co_2} is the carbon emission factor generated per unit of distance traveled by an electric vehicle user, η_e is the charging efficiency of the electric vehicle, θ is the rate of line loss in electric power transmission, and E_{100km} is the 100-kilometer power consumption of the electric vehicle. G is the set of electric energy structure types covered by the region, EF_g is the full life cycle carbon emission factor per unit of electricity generation for g form of generation, and EQ_g is the electricity generation capacity for g form of generation.

(5) Maximize the service capacity of electric vehicle charging stations, i.e:

$$\max F_6 = R \tag{12}$$

In this study, a charging service capability assessment model is constructed to assess the service capability of charging stations for charging demand points. The model first calculates the service capacity that all alternative charging stations can provide for a single demand point, and then assigns and sums up the service capacity that all charging demand points can obtain to obtain the overall service capacity value that the charging station can provide to all charging demand points. The expression is:

$$R = \sum_{j=1}^{J_q} R_j v_j \tag{13}$$

Due to the different demand at different demand points, the weight of the service capacity that can be received at all charging demand points when assigning the sum should be related to the number of electric vehicles with fast charging demand at that demand point, v_j expressed as:

$$v_j = \frac{n_j P}{\sum_{j=1}^{s} n_j P} \tag{14}$$

Meanwhile, in Eq. (13), R_j denotes the service capacity received by demand point j. When a charging station builds more piles, the closer the distance to the demand point and the road is smooth, and at the same time, the fewer electric vehicles with fast charging demand at the demand point, then for any electric vehicle with fast charging demand within the demand point, the greater the service capacity provided by the station will be. From this, the quality of charging service that can be received at that demand point can be assessed. The expression for this is:

$$R_j = \sum_{i=1}^{I_\alpha} \frac{A_i N_i P_{ij}}{d_{ij} \mu_{ij} n_j P} \tag{15}$$

where P is the probability of an electric vehicle with fast charging demand. To simplify the model, this study assumes that EV users with fast-charging demand will prioritize charging at charging stations that are closer to them, so if the distance d_{ij} between charging station i and demand point j is smaller, the probability of the charging station i being able to provide service to demand point j will be larger. Therefore, the probability P_{ij} that the charging station i can serve the demand point j, is expressed as:

$$P_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{j=1}^{J} \frac{1}{d_{ij}}} \tag{16}$$

II. A. 2) Constraints

The charging service provided by the charging station needs to fully satisfy the user's needs, so this study formulates a number of key constraints as follows:

(1) Satisfy user charging needs:

$$y_{ij} \leq Y_j, \forall i \in I, \forall j \in J \tag{17}$$

The above equation represents that in the case of assigning demand points to the selected charging station, the selected station has sufficient capacity to meet the charging needs of each demand point.

(2) Each demand point is within the service area of the charging station, ensuring comprehensive charging coverage, i.e:

$$\sum_{j \in J} y_{ij} Y_j \geq 1, \forall i \in I \tag{18}$$

(3) Limitations on the number of charging piles, viz:

$$N_{\min} \leq N_j \leq N_{\max} \tag{19}$$

where $N_{\max}$ is the maximum number of charging piles to be constructed inside power station j and $N_{\min}$ is the minimum number of charging piles to be constructed inside power station j.

(4) A demand point can only travel to one charging station to receive the service, i.e:

$$\sum_{j=1}^{J} y_{ij} = 1, \forall i \in I \tag{20}$$

(5) The number of charging stations to be constructed, viz:

$$\sum_{j} y_j = V \tag{21}$$

where V represents the number of charging stations to be constructed.

(6) Charging mileage distance limitation:

In the charging station siting strategy, the charging demand in emergency situations becomes a factor that must be considered because the remaining power status of the trolley users when they generate charging demand is usually not clear. In order to ensure that users can obtain charging services in a timely manner, the distance limitation from the point of charging demand to the charging station needs to be considered in the siting strategy to ensure that users can reach the charging station in case of emergency. Then:

$$d_{ij} \le d_{\max} \tag{22}$$

where d_{ij} represents the distance from the charging demand point i to the charging station j and $d_{\max}$ represents the anxiety charging distance.

(7) Charging service capacity constraint:

Considering the limited number of charging equipments at the charging station and the occupancy time of charging equipments by electric vehicles during the charging process, the charging demand that the charging station can satisfy in a certain cycle is limited. Then:

$$\sum_{i=1}^{I} a_i \le t_d \mu \tag{23}$$

II. B. Calculation of the number of charging piles and model expression

II. B. 1) Calculation of the number of charging piles

In the process of analyzing the daily charging demand of electric vehicles, the traffic flow at intersections is calculated according to the number of cars passing through the intersection node, and the number of chargers equipped in the fast charging station is further calculated. Considering that the cars at the intersection nodes are possible to come from two directions, the direction of outflow or inflow to the node should be selected as a uniform criterion when counting the number of cars at a node to avoid double counting.

In time period T, if the number of intersections in the planning area of a fast charging station i is n_i, then the number of chargers that should be equipped in the fast charging station is:

$$m_i = \left[\frac{\sum_{j=1}^{n_i} (q_{jcar} S_{car} + q_{jbar} S_{bar})(\rho + 1)}{P k_x T_v k_i} \right] \tag{24}$$

where [] denotes the rounding operation, S_{car}, S_{bus} denote the average charging capacity of the electric vehicle, ρ denotes the charging power margin of the fast charging station, P denotes the rated power of the charging machine, and k_x denotes the average charging efficiency of the charging machine in the fast charging station, respectively.

II. B. 2) Optimizing model expressions

In summary, the research objectives of electric vehicle charging station siting are to minimize the investment cost of the charging station, maximize the comprehensive user satisfaction and minimize the carbon emissions, and the mathematical expressions of the siting model are as follows:

(1) Objective function:

Minimizing charging station investment cost is expressed as:

$$\min C = \sum_{j=1}^{J} y_j \left(\frac{r_0 (1+r_0)^n}{(1+r_0)^n - 1} (C_{j1} + C_{j2}) + \eta C_{j2} \right) \tag{25}$$

Maximize overall user satisfaction as:

$$\max F = w_1 \sum_{i \in I} \sum_{j \in J} q_i f_1(d_{ij}) Y_{ij} + w_2 \sum_{i \in I} \sum_{j \in J} q_i f_2(t_j) Y_{ij} \tag{26}$$

The minimum carbon emissions are:

$$\min T = 893\sum_{j} E_{ECR} * d_{ij} * q_i * Y_{ij} \tag{27}$$

(2) The constraints can be expressed as follows:

$$Y_{ij} \le y_j, \forall i \in I, \forall j \in J \tag{28}$$

$$\sum_{J} Y_{ij} y_j \ge 1, \forall i \in I, \forall j \in J \tag{29}$$

$$N_{\min} \le N_j \le N_{\max} \tag{30}$$

$$N_{cgl.j} \in N, \forall j \in J \tag{31}$$

$$\sum_{J} Y_{ij} = 1, \forall i \in I \tag{32}$$

$$\sum_{j} y_j = M \tag{33}$$

$$\lambda_j < \mu_i N_{cgl.j}, \forall j \in J \tag{34}$$

$$y_j = \begin{cases} 0 & \text{Do not build a charging station at the candidate point } j \\ 1 & \text{Build a charging station at the candidate point } j \end{cases} \tag{35}$$

$$Y_{ij} = \begin{cases} 0 & \text{Demand point } i \text{ does not go to the candidate charging station point } j \text{ for charging} \\ 1 & \text{Demand Point } i \text{ goes to the candidate charging station point } j \text{ for charging} \end{cases} \tag{36}$$

Since the objective function and constraints have been described in detail in the previous section, we will not repeat them here, and the detailed information of the specific explanatory notes can be found in the previous section.

The above model is a multi-objective non-linear integer planning model, which can be transformed into a single-objective planning model by linear weighting. Since the optimization objectives of the model are minimization of construction cost, maximization of comprehensive satisfaction and minimization of carbon emission, in order to ensure the consistency of the optimization direction, the weight of minimization of the index is assigned as positive, and the weight of maximization of the index is assigned as negative. Therefore, the objective function of the single-objective planning model after linear weighted transformation is as follows:

$$\min Z = \xi_1 Z_1 - \xi_2 Z_2 + \xi_3 Z_3 \tag{37}$$

where ξ_1 is the weighting coefficient of the investment cost, ξ_2 is the weighting coefficient of the comprehensive satisfaction, ξ_3 is the weighting coefficient of the carbon emission, and $\xi_1 > 0, \xi_2 > 0, \xi_2 > 0, \xi_1 + \xi_2 + \xi_3 = 1$. Then:

$$Z_1 = \frac{C - C_{\min}}{C_{\max} - C_{\min}} \tag{38}$$

$$Z_2 = \frac{F - F_{\min}}{F_{\max} - F_{\min}} \tag{39}$$

$$Z_3 = \frac{T - T_{\min}}{T_{\max} - T_{\min}} \tag{40}$$

where $C_{\min}, C_{\max}$ is the minimum and maximum of the investment cost C, $F_{\max}, F_{\min}$ is the minimum and maximum of the comprehensive satisfaction F. $T_{\min}, T_{\max}$ are the minimum and maximum values of carbon emissions T.

III. Model solving

As a new energy vehicle with many advantages such as low pollution, low energy consumption and high energy utilization, electric vehicles have received great attention from governments, enterprises and consumers. However, the limited range of electric vehicles makes drivers easily fall into the trouble of mileage anxiety, which restricts the use of electric vehicles in the scene. Scientific and reasonable planning and construction of electric vehicle charging facilities is an effective way to alleviate drivers' mileage anxiety and expand the use of electric vehicles.

III. A. Forbidden search algorithm and genetic algorithm

III. A. 1) Taboo Search Algorithm

The Taboo Search (TS) algorithm mainly consists of the coding method and fitness function, initialization of the solution, neighborhood motion and neighborhood solution, taboo table, selection strategy, amnesty and pause criteria. The algorithm circumvents the multiple loops that may appear to happen during the search process by setting up a taboo table, the recent search process is stored directly in the taboo table, preventing the algorithm from searching, which means that a good solution in the taboo table continues to be passed as the initial solution for the next generation, and the taboo table will be used to replace the iterations continuously updated until the set number of iterations is completed. Taboo table search algorithms can then receive poorer solutions, so they have a better ability to climb the hill. In addition to this, taboo search algorithms are able to balance the decentralized search throughout the whole globe and the centralized search in local regions relatively well [28].

The general iterative idea of taboo search algorithms is to select a certain number of candidate solutions in the neighborhood of the current solution by generating an initial solution that can be used as the current solution of the algorithm, and if the optimal candidate solution is much more adaptive than the historically optimal solution, then the solution is accepted by the algorithm regardless of whether it is located in the taboo table or not. Conversely, if the existence of candidate solutions of this type is not determined, the current solution can be replaced by selecting candidate solutions that do not exist in the taboo table and adding their corresponding moves to the taboo table. The algorithm stops by repeating the above method over and over again until the stopping criterion is reached [29].

In this paper, the objective function value is used as the amnesty criterion for the taboo search algorithm, and if the objective function value of a candidate solution is better than the historical optimum, the solution is accepted regardless of whether the candidate solution is in the taboo table or not. The maximum number of iterations is used as the stopping criterion, i.e., the algorithm stops when the iterations reach a specified number of times.

III. A. 2) Genetic algorithms

Genetic Algorithm (GA) is a stochastic global search optimization algorithm based on the principles of natural selection and genetics. It simulates the process of biological evolution in nature and solves complex optimization problems by simulating the inheritance and evolution of organisms. The algorithm optimizes the solution step by step by simulating replication, crossover and mutation in the process of biological evolution, and finally finds the optimal or near-optimal solution of the problem. Genetic algorithm can deal with complex nonlinear problems, and the search of this algorithm does not depend on the gradient problem and thus has strong parallel search ability and good robustness [30]. The basic process of genetic algorithm is as follows:

(1) Coding. The encoding operation is the process of representing the solutions of a problem as chromosomes. Encoding maps the solution space of the problem to a discrete search space in the genetic algorithm so that the genetic algorithm can search and optimize these solutions. Let the range of values of a particular parameter be $[U_1, U_2]$, and the formula for using a binary encoding of length k for this parameter is as follows:

$$\begin{gathered} 000\cdots000 = 0 \to U_1 \\ 000\cdots001 = 1 \to U_1 + \delta \\ 000\cdots010 = 2 \to U_1 + 2\delta \\ \vdots \\ 111\cdots111 = 2^k - 1 \to U_2 \end{gathered} \tag{41}$$

where $\delta = \dfrac{U_2 - U_1}{2^k - 1}$.

(2) Initializing the population. The initialize population operation involves randomly generating an initial set of individuals and is the starting point of the algorithm's search space.

(3) Fitness evaluation. This operation is used to measure the degree of superiority of individual solutions and is accomplished through the fitness function. The fitness function is used to evaluate each individual and gives a numerical value that indicates the degree of merit of the individual in the problem solution space. The size of the individual's fitness is appropriately changed at different stages of the algorithm by means of fitness scale transformations to achieve the purpose of avoiding the weakening of competition caused by comparable fitnesses among groups. Commonly used scale transformation methods include linear scale transformation, multiplicative

power scale transformation and exponential scale transformation, etc., and their transformation formulas are as follows:

$$F' = aF + b \tag{42}$$

$$F' = F^k \tag{43}$$

$$F' = e^{-\beta F} \tag{44}$$

where F' is the post-transformation fitness scale, F is the pre-transformation fitness scale, a is the scaling coefficient, b is the translation coefficient, F^k is the k power of the pre-transformation fitness scale, e is a natural constant, and β is a coefficient, the smaller β is, the more the individual with a high fitness scale before the transformation the smaller β is, the greater the difference between the new fitness of the individual with higher fitness before transformation and the new fitness of the other individuals.

(4) Selection. Selection refers to the selection of some individuals from the current population as the parents of the next generation of the population according to the value of the fitness function. Commonly used selection strategies include roulette selection, competitive selection and ranking selection. Taking the roulette selection strategy as an example, the formula for the probability that individual i is selected is as follows:

$$P_i = \frac{f_i}{\sum_{k=1}^{M} f_k} \tag{45}$$

where M is the population size and f_i is the fitness of individual i.

(5) Crossover. This operation produces a new individual by mimicking the process of genetic recombination in biological evolution by exchanging and combining the chromosomes of two parent individuals.

(6) Mutation. Mutation randomly changes the chromosomes of individuals by simulating the process of mutation in biological evolution, introducing new genetic changes to produce new individuals and increase the diversity of the population. The mutation operation helps to avoid falling into local optimal solutions and improves the global search ability of the algorithm. After determining the location of the mutation, the chromosome of the individual is randomly changed, and the commonly used mutation operations are bit mutation, uniform mutation and Gaussian mutation.

(7) Decoding. Decoding refers to the conversion of a chromosomal representation of an individual into a solution or representation of a problem.

The solution of the target problem is accomplished iteratively by repeating the selection, crossover and mutation operations over and over again.

III. B. Charging station siting optimization model solution

III. B. 1) Hybrid Genetic Taboo Search Algorithm

Genetic algorithm is a highly parallel, stochastic and adaptive optimization algorithm based on biological evolution and selection mechanism, which has strong robustness and global search ability, but the late convergence is slow, the computational efficiency is low, and it is easy to fall into the local optimum.

Taboo search algorithm is a neighborhood search algorithm based on taboo technology, which is characterized by the use of taboo technology, i.e., it is forbidden to repeat the previous work, thus jumping out of the local optimum. However, the taboo search algorithm also has some defects, such as a strong dependence on the initial solution, serial operation on only one solution, and low search efficiency.

Based on the above characteristics, a hybrid genetic taboo search (GATS) algorithm is designed, which firstly adopts the genetic algorithm to conduct a large-scale search in the global space, i.e., the initial population traverses most of the regions of the solution space in a parallel manner, and the optimization results are stabilized in the partially optimized regions of the solution space at the termination of the iteration. Then from each individual in the optimization region, the taboo search algorithm is used to conduct a small search in the local space, thus delaying or avoiding the genetic algorithm to fall into the local optimum, and improving the algorithm's ability to find the best. The hybrid algorithm effectively makes up for the defects of poor local search ability of the genetic algorithm and weak global search ability of the taboo search algorithm, which is strongly dependent on the initial solution.

III. B. 2) Optimized model solution process

Figure 1 shows the specific flow of the GATS algorithm for solving the charging station siting optimization model. Its specific steps are as follows:

Step1 Initialize to generate N feasible solutions, N is the population size.

Step2 Evaluate the fitness value of each individual in the population.

Step3 Judge whether the population reaches the termination condition, if so, output the best solution, otherwise go to Step4.

Step4 Pick a selection strategy to select the next generation of population.

Step5 Perform crossover operation according to crossover probability Pc to produce two new individuals.

Step6 Perform mutation operation by mutation probability Pm to produce two new individuals.

Step7 Optimize the generated new individuals with taboo search algorithm.

Step8 Generate new generation population and return to Step3.

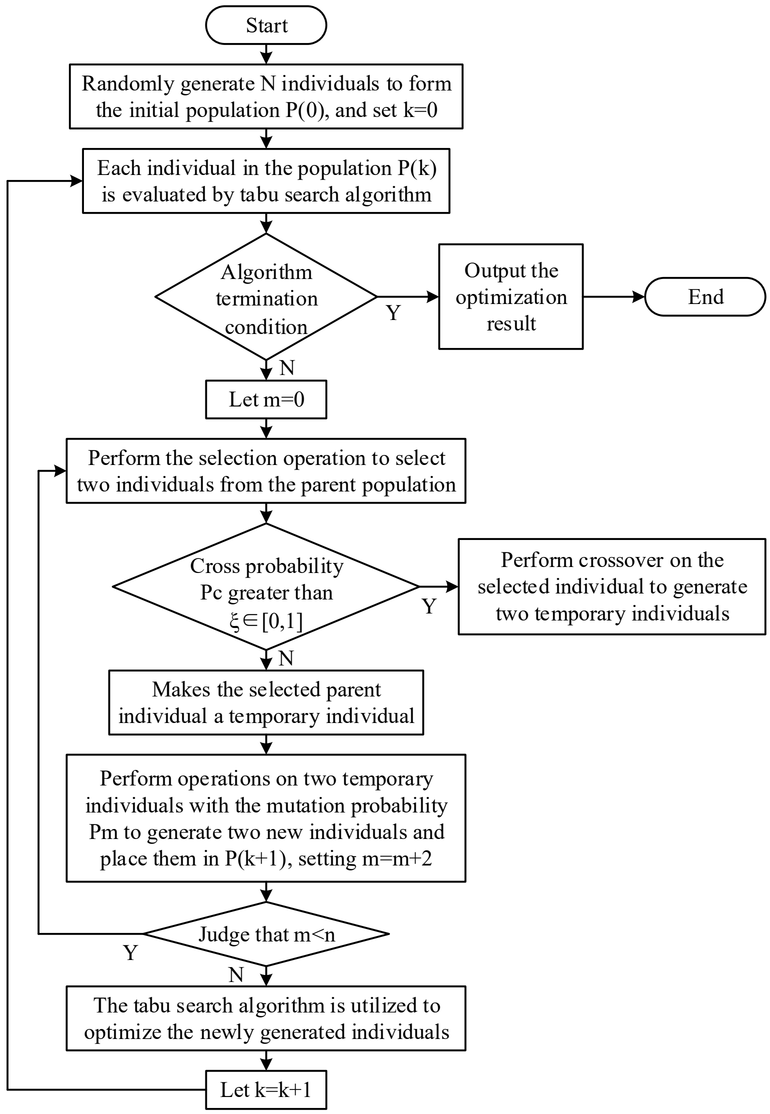

Figure 1: Optimize the solution process of the model

IV. Analysis of examples

With increasing ecological concerns and decreasing dependence on fossil fuels, electric vehicles have received much attention as a sustainable transportation solution. Electric vehicles are popular due to their eco-friendly features, however, their limited energy storage capacity restricts the driving distance, so efficient energy utilization is crucial. In order to ensure that EVs can obtain supplementary energy in a timely manner, a charging station location optimization method based on the GATS algorithm is proposed. This not only shortens the time for users to travel to the charging station, but also reduces the waiting time during the charging process, thus effectively enhancing the efficiency and convenience of the charging service. At the same time, optimizing the layout and capacity of the charging station also helps to improve the charging experience of users and enhance their recognition and satisfaction of electric vehicles.

IV. A. Algorithm performance comparison

In order to verify the effectiveness and practicality of the GATS algorithm, it is based on seven benchmark test functions (F1~F7), in which the functions F1~F4 serve to test the speed of convergence of each optimization algorithm in the process of full iteration, and the functions F5~F7 serve to test whether the algorithms are able to get rid of and escape from the local space effectively. The performance is compared with the algorithms of Gray Wolf Algorithm (GWO), Particle Swarm Algorithm (PSO), Harris Hawk Algorithm (HHO) and Whale Optimization Algorithm (WOA) which have better optimization performance, and the test functions include single-peak function and multi-peak function. In order to fairly verify the effectiveness of the GATS algorithm, the test is carried out in the same operation environment, and the simulation is completed by using MATLAB software, and the parameters of each algorithm are set as in the existing related literature, with the general condition set to the same, the number of populations is 50, and the number of iterations is 200.

Table 1 shows the test results of each single-peak test function. Since the single-peak function has only one optimal solution globally, it can be well used to test the convergence performance of many algorithms, and from the data in the table, it can be clearly seen that the GATS algorithm is below the remaining four algorithms, infinitely close to the theoretical optimum, and compared with the remaining four algorithms, the convergence accuracy is obviously improved a lot. Secondly, the convergence accuracy of GWO algorithm and PSO algorithm is almost the same, and the optimization effect and solving ability of HHO algorithm and WOA algorithm are equally divided, and all of them are smaller than GWO and PSO algorithms, and the time consumed for solving is shorter. In summary, it can be concluded that for optimizing the single-peak function, the GATS algorithm shows more obvious advantages than several other algorithms in various performance indicators.

Table 1: Comparison of Unimodal function results

Function	Algorithm	Means	STD	Min	Max
F1	GWO	1.75E-03	8.25E-04	4.35E-04	3.45E-03
	PSO	1.51E+03	1.29E+03	4.16E+02	4.15E+03
	WOA	1.42E-10	3.84E-12	3.75E-15	1.23E-11
	HHO	4.96E-25	1.54E-25	5.36E-34	4.86E-22
	GATS	2.74E-163	0.01E+00	3.99E-208	2.71E-172
F2	GWO	3.36E-02	1.04E-02	2.41E-02	5.99E-02
	PSO	4.23E+02	1.45E+02	2.37E+02	6.23E+02
	WOA	4.51E-09	5.68E-09	2.34E-11	1.45E-08
	HHO	1.37E-13	2.22E-13	7.63E-15	5.53E-13
	GATS	4.53E-80	9.57E-90	2.78E-102	2.36E-89
F3	GWO	4.15E+05	9.31E+04	2.88E+05	5.91E+05
	PSO	9.36E+05	2.85E+05	5.63E+05	1.58E+06
	WOA	1.26E+06	4.31E+06	6.31E+06	1.97E+07
	HHO	8.15E-14	1.55E-16	2.15E-24	4.99E-16
	GATS	1.72E-135	4.21E-135	9.05E-63	1.31E-131
F4	GWO	6.08E+01	1.62E+01	1.45E-04	5.16E+02
	PSO	3.27E+03	9.83E+03	4.15E+01	3.16E+04
	WOA	1.37E-15	3.45E-15	1.82E-18	1.13E-14
	HHO	1.93E-24	6.06E-24	1.15E-28	1.96E-25
	GATS	0.01E+00	0.01E+00	0.01E+00	0.01E+00

Table 2 shows the results of the multi-peak function test. The multi-peak function has more than one local extreme and can be used to test the ability of individual algorithms to get rid of local domains. So that the algorithms want to seek the optimal solution, they have to eliminate multiple local optimal solutions first in order to find the global optimal solution. From the results of the test functions from F5 to F7, it can be seen that the GATS algorithm values are below the remaining four algorithms, and the convergence accuracy is infinitely close to the theoretical optimum, and the remaining four algorithms are all trapped in the local optimum when the number of iterations reaches a certain number. Secondly, the WOA algorithm and HHO algorithm show more outstanding performance compared to the GWO algorithm and PSO algorithm in solving the multi-peak function problem, and the advantage is very obvious. In summary, the GATS algorithm is able to avoid local extremes in solving the multi-peak function problem, which greatly reduces the probability of falling into the local domain, and then converges quickly to the global, showing a very obvious advantage compared with the other four algorithms.

Table 2: Comparison of Multimodal function results

Function	Algorithm	Means	STD	Min	Max
F5	GWO	3.56E+02	1.32E+02	1.65E+02	5.31E+02
	PSO	7.15E+02	1.95E+02	3.75E+02	9.43E+02
	WOA	1.06E-02	3.28E-02	2.26E-14	1.05E+01
	HHO	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	GATS	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F6	GWO	5.72E-02	5.11E-02	2.19E-02	1.72E+01
	PSO	1.26E+02	1.64E+01	1.05E+02	1.52E+02
	WOA	3.81E-08	9.63E-08	1.74E-09	3.15E-07
	HHO	2.35E-14	5.65E-14	4.46E-16	1.82E-11
	GATS	8.86E-16	0.00E+00	8.86E-16	8.86E-16
F7	GWO	1.24E+02	2.84E+01	7.75E+01	1.74E+02
	PSO	6.33E+03	9.41E+02	4.52E+02	7.95E+03
	WOA	2.15E-12	4.73E-12	1.42E-15	1.54E-11
	HHO	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	GATS	0.00E+00	0.00E+00	0.00E+00	0.00E+00

To summarize, the GATS algorithm has better convergence performance with smoother convergence curves and few larger inflection points. Compared with four algorithms, namely, Particle Swarm Algorithm (PSO), Whale Optimization Algorithm (WOA), Gray Wolf Algorithm (GWO), and Harris Hawk Algorithm (HHO), the GATS algorithm has a higher convergence accuracy and faster convergence speed. The test function comparison results indicate that the GATS algorithm can effectively get rid of the local extremes in solving the multi-peak function, and then converge quickly to the global optimal solution, and the global search ability is effectively improved, so it can effectively solve the multi-objective optimization problem.

IV. B. Comparison of site selection optimization results

In order to verify the effectiveness of the proposed charging station siting optimization method, the optimization model and algorithm given in the paper are used to determine the siting of the charging station using the IEEE30 node system as an example. Assuming that each node is a potential site for a charging station, the model and optimization parameters of the charging station are designed according to the relevant literature.

The site selection is optimized separately for two scenarios whether the charging station has vehicle-to-grid (V2G) mode or not, in the scenario without V2G mode, all the charging stations work only in grid-to-vehicle (G2V) mode. In the scenario with V2G control mode, 15% of the EVs in the charging stations work in V2G mode and only 1 charging head per charging station has V2G capability. The results of the siting optimization in different scenarios are shown in Table 3, and the trend of the voltage change of each node in the IEEE30 system is shown in Fig. 2.

Without the configuration of charging stations, the total line network loss of the original IEEE30 node system is 225.76 kW, and the minimum and maximum values of the node voltages are 0.9381 p.u. and 0.9946 p.u., respectively. In the scenario without V2G mode, with the objective function of simultaneously reducing the installation cost of charging station and network loss, considering the constraints of current, voltage and power balance, the optimization is carried out by the GATS algorithm, and finally nodes 3,12,15,17,28 are obtained as the optimal locations of charging stations. At this point, the total cost of the system in terms of busway network loss and charging station installation is 2,358,300 kW and 2,431,800 Yuan, respectively. In the scenario with V2G mode, keeping the objective function and constraints unchanged, the optimization through the GATS algorithm finally obtains the optimal location of the charging station at nodes 3,4,15,16,17, and at this time, the system's bus network loss and total cost of installation of charging stations are 2,007,100 kW and 2,514,700 yuan, respectively. The number of charging station sites without V2G mode and with V2G mode are both five, and the node locations are not exactly the same. The latter has less influence on the system voltage drop due to the power return of V2G, and the bus network loss is smaller, but the total installation cost of the charging station is slightly higher than that of the former. Overall, the optimized site selection without V2G mode is more beneficial to the investor, while the optimized site selection with V2G mode is more beneficial to the operator.

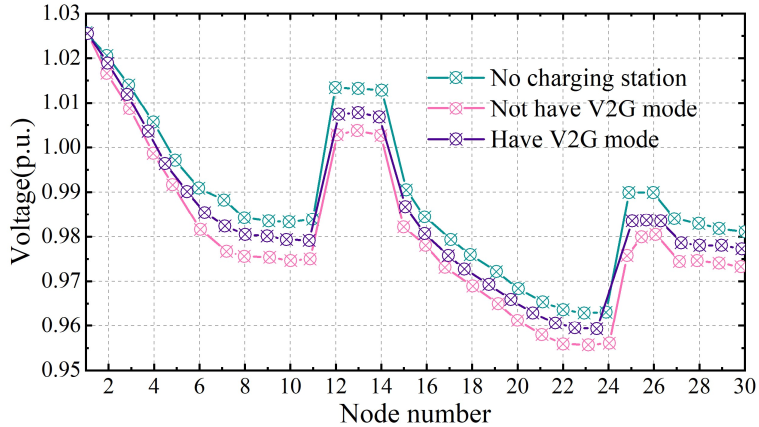

Figure 2: The voltage variation trend of each node

Table 3: Comparison of site selection optimization results

Parameters	Not have V2G mode	Have V2G mode
Site selection node	3,12,15,17,28	3,4,15,16,17
Min node voltage/(p.u.)	0.955	0.959
Max node voltage/(p.u.)	1.012	1.028
Bus network loss /kW	235.83	200.71
Total installation cost/*10^5 yuan	243.18	251.47

IV. C. Economic benefits and carbon emissions

According to the ownership of electric vehicles and the maximum service capacity and minimum service capacity of charging stations, after reasonable planning of pre-built charging stations for 4 to 12, and respectively, the whole society economic cost and carbon emissions as the objective function of single-objective decision-making, the GATS algorithm is used for the selection of the location of the charging stations for electric vehicles. Setting the population size and other related parameters, the maximum number of iterations is 500, and 40 independent runs are performed to obtain the optimal value, average value and error of constructing different numbers of charging stations. Table 4 shows the average value and error of the social economic cost and carbon emission for 40 independent runs to obtain the optimal solution by taking the social economic cost as the decision-making objective, which corresponds to the social economic cost and carbon emission. Table 5 shows the mean and error of the carbon emissions and the socio-economic cost of the optimal solution obtained by using the carbon emissions as the decision objective, and the mean and error of the carbon emissions and the socio-economic cost for 40 independent runs.

In the case of using the total social economic cost as the decision-making objective, the total social economic cost includes the annual investment cost, the annual operation and maintenance cost, the annual vehicle loss cost and the annual charging cost, of which the annual charging cost and the annual vehicle loss cost are affected by the distance traveled by the vehicle, but both of them have a small proportion in the total social economic cost, that is to say, when the total social economic cost obtains the optimal value, the carbon emission can obtain the relatively optimal value. When carbon emissions as the decision-making objective, carbon emissions only consider the distance traveled by the vehicle, and does not take into account the cost, so that the change of the whole social economic cost is especially obvious, when carbon emissions to achieve the optimal value, the economic cost is larger. From the analysis of the data in Tables 4 and 5, it can be seen that when a single objective is used as the decision-making objective, the value of the other objective varies greatly, and the difference in the results obtained is obvious, and when the decision-making objective obtains the optimal value, the other objective may obtain a worse function value.

Table 4: Make decisions based on the economic cost of the entire society

Number	Economic cost/*10^5 yuan			Carbon emissions/kg		
	Optimal	Means	Error	Optimal	Means	Error
4	1133.08	1127.77	5.31	831261.27	801970.12	29291.15
5	1167.97	1158.64	9.33	719668.38	642750.25	76918.13
6	1185.21	1163.53	21.68	788322.18	742208.23	46113.95
7	1196.67	1189.75	6.92	768759.05	728665.21	40093.84
8	1231.75	1214.29	17.46	857244.31	823647.92	33596.39
9	1278.15	1252.49	25.66	828351.25	754762.34	73588.91
10	1378.04	1354.57	23.47	812097.36	788613.87	23483.49
11	1477.72	1451.91	25.81	829121.19	791091.14	38030.05
12	1492.54	1468.62	23.92	694349.28	682415.17	11934.11

Table 5: Make decisions based on carbon emissions

Number	Carbon emissions/kg			Economic cost/*10^5 yuan		
	Optimal	Means	Error	Optimal	Means	Error
4	753022.13	740053.92	12968.21	1265.87	1227.46	38.41
5	750616.15	730039.71	20576.44	1351.66	1302.18	49.48
6	739115.29	726948.07	12167.22	1450.74	1378.31	72.43
7	725383.71	710087.63	15296.08	1640.82	1550.49	90.33
8	687209.67	657049.68	30159.99	1741.41	1637.98	103.43
9	678169.82	658998.59	19171.23	2098.07	2296.05	-197.98
10	664921.43	641837.05	23084.38	1978.64	1767.46	211.18
11	639531.73	610465.17	29066.56	1928.67	1513.39	415.28
12	637079.6	608948.27	28131.33	2163.74	2839.17	-675.43

V. Conclusion

The optimized charging station siting scheme shows significant advantages on several levels. The layout of EV charging stations optimized by the GATS algorithm effectively reduces the line grid losses of the system by up to 15%. In the scenario where V2G mode is selected, the optimized siting plan further reduces grid losses and lowers carbon emissions to optimal levels. At the same time, the total cost of charging station construction is kept under control, minimized by about 10%. When the society-wide economic cost is used as the decision-making objective, the optimal solution is to construct five charging stations, which requires an economic cost of 11,679,700 yuan and a carbon emission of 719,668.38 kg. And when carbon emission is the objective, the optimal solution is the reduced carbon emission with an economic cost of 13,516,600 yuan and a carbon emission of 750,616.15 kg. The above results show that the optimization method proposed in this study can not only effectively balance the economic cost and environmental protection needs, but also provide a scientific decision-making basis for the construction of electric vehicle charging stations.

References

[1] Li, Y., Yang, J., & Song, J. (2017). Design structure model and renewable energy technology for rechargeable battery towards greener and more sustainable electric vehicle. Renewable and Sustainable Energy Reviews, 74, 19-25.

[2] Li, J., & Yang, B. (2020). Analysis of greenhouse gas emissions from electric vehicle considering electric energy structure, climate and power economy of ev: A China case. Atmospheric Pollution Research, 11(6), 1-11.

[3] Cheng, Q., & Xiong, Y. (2024). Low-carbon sustainable development driven by new energy vehicle pilot projects in China: effects, mechanisms, and spatial spillovers. Sustainable Development, 32(1), 979-1000.

[4] Fulton, L., Schäfer, A. W., & Sperling, D. (2024). Transitions to deeply decarbonized transportation and energy systems around the world: challenges and solutions. Transportation Research Part D: Transport and Environment, 104219.

[5] Mo, T., Li, Y., Lau, K. T., Poon, C. K., Wu, Y., & Luo, Y. (2022). Trends and emerging technologies for the development of electric vehicles. Energies, 15(17), 6271.

[6] Cheng, M., & Tong, M. (2017). Development status and trend of electric vehicles in China. Chinese Journal of Electrical Engineering, 3(2), 1-13.

[7] Bilal, M., & Rizwan, M. (2025). Integration of electric vehicle charging stations and capacitors in distribution systems with vehicle-to-grid facility. Energy sources, part a: recovery, utilization, and environmental effects, 47(1), 7700-7729.

[8] Ahmad, F., Iqbal, A., Ashraf, I., & Marzband, M. (2022). Optimal location of electric vehicle charging station and its impact on distribution network: A review. Energy Reports, 8, 2314-2333.

[9] Deb, S., Tammi, K., Kalita, K., & Mahanta, P. (2018). Impact of electric vehicle charging station load on distribution network. Energies, 11(1), 178.

[10] Wang, Y., Zhou, J., Sun, Y., Wang, X., Zhe, J., & Wang, H. (2022). Electric vehicle charging station location-routing problem with time windows and resource sharing. Sustainability, 14(18), 11681.

[11] Lei, L., & Liang, P. (2020, October). Location planning of electric vehicle charging station based on HPSO-TS. In Journal of Physics: Conference Series (Vol. 1650, No. 2, p. 022097). IOP Publishing.

[12] Islam, M. M., Shareef, H., & Mohamed, A. (2018). Optimal location and sizing of fast charging stations for electric vehicles by incorporating traffic and power networks. IET Intelligent Transport Systems, 12(8), 947-957.

[13] Lin, R., Ye, Z., Guo, Z., & Wu, B. (2020). Hydrogen station location optimization based on multiple data sources. International Journal of Hydrogen Energy, 45(17), 10270-10279.

[14] Ouyang, X., & Xu, M. (2022). Promoting green transportation under the belt and Road Initiative: Locating charging stations considering electric vehicle users' travel behavior. Transport Policy, 116, 58-80.

[15] Neyestani, N., Damavandi, M. Y., Shafie-Khah, M., Contreras, J., & Catalão, J. P. (2014). Allocation of plug-in vehicles' parking lots in distribution systems considering network-constrained objectives. IEEE Transactions on Power Systems, 30(5), 2643-2656.

[16] Zhang, B., Zhao, M., & Hu, X. (2023). Location planning of electric vehicle charging station with users' preferences and waiting time: multi-objective bi-level programming model and HNSGA-II algorithm. International Journal of Production Research, 61(5), 1394-1423.

[17] Sharma, S., Kaur, D., & Saxena, N. K. (2024). Investigation for size and location of electric vehicle charging station accompanying VRP index and commissioning cost. International Journal of Emerging Electric Power Systems, 25(1), 45-59.

[18] Liu, H. C., Yang, M., Zhou, M., & Tian, G. (2018). An integrated multi-criteria decision making approach to location planning of electric vehicle charging stations. IEEE Transactions on Intelligent Transportation Systems, 20(1), 362-373.

[19] Wu, Y., Yang, M., Zhang, H., Chen, K., & Wang, Y. (2016). Optimal site selection of electric vehicle charging stations based on a cloud model and the PROMETHEE method. Energies, 9(3), 157.

[20] Tungom, C. E., Niu, B., & Wang, H. (2023). NEO: Neural Demand Prediction and Evolutionary Optimization of EV Network Charging Infrastructure. In Fuzzy Systems and Data Mining IX (pp. 36-46). IOS Press.

[21] Hong, Z., & Shi, F. (2024). A multi-objective site selection of electric vehicle charging station based on NSGA-II. International Journal of Industrial Engineering Computations, 15(1), 293-306.

[22] Akbari, M., Brenna, M., & Longo, M. (2018). Optimal locating of electric vehicle charging stations by application of genetic algorithm. Sustainability, 10(4), 1076.

[23] Chen, K., & Peng, C. (2019, October). Multi-period Planning of Electric Taxi Charging Station Based on Genetic Tabu Hybrid Algorithm. In IOP Conference Series: Materials Science and Engineering (Vol. 612, No. 4, p. 042084). IOP Publishing.

[24] Jordán, J., Palanca, J., Martí, P., & Julian, V. (2022). Electric vehicle charging stations emplacement using genetic algorithms and agent-based simulation. Expert Systems with Applications, 197, 116739.

[25] Ting, C. K., Ko, C. F., & Huang, C. H. (2009). Selecting survivors in genetic algorithm using tabu search strategies. Memetic Computing, 1, 191-203.

[26] Wang, B., Zhou, Y., & Zhang, S. (2017). Multi-objective planning model of electric vehicle charging station. Information Systems and Signal Processing Journal, 2(1), 23-28.

[27] Liu, H., Li, Y., Zhang, C., Li, J., Li, X., & Zhao, Y. (2022). Electric vehicle charging station location model considering charging choice behavior and range anxiety. Sustainability, 14(7), 4213.

[28] Wu Wei,Wu Xiande,Liu Fanming,Liu Shuhao,Wang Tianzhe & Xing Zejing. (2025). Single-Pass Imaging Planning with a Hybrid Genetic Tabu Search Algorithm for Agile Earth Observation Satellites. Journal of Aerospace Engineering,38(4).

[29] Baptistin Carvin,Odile Bellenguez & Guillaume Massonnet. (2025). Tabu search for a multi-mode RCPSP with generalized precedence and sequence-dependent setup time. Computers & Industrial Engineering,205,111142-111142.

[30] Ningbo Sun. (2024). Research on energy storage charging piles based on improved genetic algorithm. Journal of Physics: Conference Series,2703(1).