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Location Selection of Charging Stations based on Improved Evolutionary Algorithms

Kuo Li*, **Yi Wang and Haiyi Pan**

Guangzhou Power Supply Bureau of Guangdong Power Grid Co. Ltd. Guangzhou City, Guangdong Province, China

Improving the efficiency of the charging network is key to the development of electric vehicles, and is also an important process in the commercialization and industrialization of electric vehicles. Ensuring the convenient layout of charging stations is important in terms of infrastructure investment, operational safety and the quality of charging stations. If the location and capacity of charging stations are not appropriate, this may affect the travel convenience of users and the planning and layout of the urban transportation network, thus affecting the wide application of electric vehicles. It may also lead to a significant increase in power consumption and a significant drop in the voltage of some nodes. The location and capacity of charging stations must be optimal for the convenience of electric vehicle users and to improve the operational benefits of charging stations. By comprehensively considering the various influencing factors of charging stations, three important indicators affecting the planning of charging stations, namely economy, average utilization rate of charging stations and charging convenience of users are constructed. The multi-objective planning model of electric vehicle charging stations was established and the designed double-layer coding method was used to optimize the evolutionary algorithm to solve the problem. Finally, an example is given to illustrate the effectiveness of the proposed model and the evolutionary algorithm for design optimization. An improved evolutionary algorithm is used to analyze a city example.

Keywords: Charging station, Location selection, Improved evolutionary algorithms

1. INTRODUCTION

Charging facilities such as charging piles, battery change stations and so on, are necessary and important supporting infrastructure for the development of electric vehicles [1]. In cases where charging facilities are newly established and the requirements of the energy supply network have not yet been determined. The rapid establishment of a number of public charging stations can have an important effect on the promotion and popularization of electric vehicles [2,3]. In the process of electric vehicle technology research, development and manufacturing, the construction of electric vehicle related infrastructure must be properly considered [4,5]. The systematic construction of electric-vehicle-related support facilities is crucial to the expansion of the electric vehicle market [6]. With the continuous development and use of electric vehicles, the planning and construction of charging stations will become large-scale and networked, so it is urgent to study the optimal layout of charging stations. In this study, many factors affecting the planning of electric vehicle charging stations are comprehensively considered [7]. To ensure the economic optimization of station construction, the utilization rate of charging stations and the charging convenience of users are also taken as the optimization goals, and a multi-objective overall planning model is established to achieve a balance between the three indicators.

2. MODEL ASSUMPTIONS

The configuration of charging machines in a charging station should not only meet the charging needs of users, it should

*Address for correspondence: Kuo Li, Guangzhou Power Supply Bureau of Guangdong Power Grid Co., Ltd. Guangzhou City, Guangdong Province, China., Email: likuoei@126.com

also avoid a situation where resources are idle. In this study, the average utilization rate of charging stations is taken as an optimization goal for the location selection of charging stations to determine the optimal location of charging stations [8]. The convenience of charging will directly affect the purchase behavior of consumers in relation to electric vehicles. Therefore, the convenience of charging stations is also an important aspect to consider in the location selection of charging stations. On this basis, the model assumptions include:

(1) The candidate points of charging stations all consider the demand distribution and meet the environment and safety conditions of charging station construction;

(2) The demand at each demand point is related to the total number of EV charging needs in this small area and represents the number of vehicles that need to be charged every day;

(3) In a fixed period of time, users at each demand point can only go to the same charging station for charging;

(4) Within the permissible range of charging station configuration, the distribution between demand points and charging stations will be conducted in accordance with the nearby place.

3. MODEL BUILDING

3.1 Objective Functions

The objective functions required for model construction specifically refer to the economic index, the average utilization index of the charger, and the user's charging convenience index.

(1) Economic index

The economy proposed in this paper includes the annual investment and operation costs of charging stations and the annual charging costs of users. The mathematical expression is as follows:

$$\min F = \min(F_1 + F_2) \tag{1}$$

① Annual investment and operation costs of charging stations

Annual investment operating costs include two items: annual fixed investment and annual operating costs. The fixed investment includes the initial construction and installation costs of chargers, distribution transformers and other auxiliary equipment, land acquisition, auxiliary road construction and so on [i]. Operating costs include the daily operation and maintenance of charging stations and staff salaries.

The scale of a charging station is measured by the number of chargers, which is the main determinant of fixed investment in a charging station. The greater the number of charging machines, the more vehicles can be served, so the larger the area of use, the greater the corresponding land acquisition costs, equipment purchase costs and other fixed costs. Also, the more managers which are needed, the higher the operational and maintenance costs. Therefore, both fixed investment and operating costs are functions of the number of chargers. Annual investment operating expenses can be expressed as:

$$\mathrm{F}_1 = \sum_{j \in J} C_j \left[T(N_j) \frac{r_0(1+r_0)^{n_{year}}}{(1+r_0)^{n_{\text{year}}} - 1} + Y(N_j) \right] \tag{2}$$

where J is the set of selected candidate points of charging stations; $C_j$is a 0–1 variable, where, if a charging station is established at candidate station j, then C_j is 1; otherwise, it is 0;N_j is the number of chargers to be built at candidate stations j; $T(N_j)$ is the fixed investment cost function of candidate station j; $Y(N_j)$ is the annual operating cost of candidate station j; r_0 is the discount rate; and n_{0year} is the depreciation life of the charging station.

② Annual charging costs of users

The charging costs of users include indirect costs such as electric power consumption for charging, the replacement costs of battery loss and the economic benefits caused by charging occupation time and so on. These fees are mainly determined by the distance between the charging demand point and the charging station and the user's electricity bill at the time of charging. The user's annual charging cost can be expressed as:

$$\mathrm{F}_2 = 365 \left[\omega \sum_{j \in J} \sum_{i \in I} X_{ij} n_i \lambda d_{ij} + k \sum_{i \in I} n_i \right] \tag{3}$$

In formula 3, I is the collection of charging demand points; ω is the charging cost per unit distance during charging; X_{ij} is a 0-1 variable, where if the demand point i receives service at the candidate point j, then X_{ij} is 1, otherwise, it is 0; n_i is the number of vehicles requiring quick charging every day at the demand point; λλ is the non-linear coefficient of the urban road; d_{ij} is the spatial straight-line distance between the demand point and the candidate station; and k is the average price of a fast charging electric car at this stage.

The average utilization index of the charger

An excessive number of chargers in a charging station is bound to result in idle resources. However, if the number of chargers is too small, the charging station will not meet the needs of users and it will make the queuing time for charging too long, resulting in inconvenience for users [ii]. Therefore, ensuring the utilization rate of the charging machine in the charging station is the key index to investigate the constant capacity of a charging station.

Charging stations are not busy all the time and there will be certain vacancy periods (for example, users generally charge their cars during the day so charging stations are generally empty at night). To illustrate this, we define the following symbol:

η is the user arrival rate, that is, the average arrival rate of electric vehicles to charging stations, and the number of electric vehicles arriving at charging station j per hour is calculated as follows:

$$\eta_j = \frac{K \cdot \sum_{i \in I} X_{ij} n_i}{T} \tag{4}$$

In formula 4, K is the proportion of vehicles serving the non-vacant period compared to the number of vehicles serving the full time period; T is the duration of the non-vacancy period; μ is the average service rate (or the average charging capacity of the charger), which is the average number of vehicles a charger can serve per hour.

Therefore, the average utilization ratio of the charger can be expressed as:

$$\lim_{\varphi} : \varphi = \frac{1}{M} \cdot \sum_{j \in J} \frac{\eta_j}{N_j \mu} \tag{5}$$

In formula 5, M is the number of charging stations to be built.

User's charging convenience index

Charging stations are constructed to provide a convenient service to users, so the convenience of charging is an important indicator of the location of charging stations. In this paper, the charging convenience of users is represented by the average distance of each user to the corresponding charging station. The charging convenience of users can be expressed as:

$$\min \sigma = \frac{\sum_{j \in J} \sum_{i=I} X_{ij} d_{ij} n_i}{\sum_{i \in I} n_i} \tag{6}$$

3.2 Constraint Conditions

Constraint conditions include variable constraints, inequality constraints of charging station charger configuration, inequality constraints of distance between charging stations and inequality constraints of the distance between charging demand points and charging stations.

(1) Variable constraints

Users with the same charging demand point can only charge at the same charging station:

$$\sum_{j} X_{ij} = 1 \forall_i = 1 \tag{7}$$

Charging services can only be provided for users if charging stations are selected and established at the candidate points:

$$X_{ij} < C_j, \forall_i \in I, j \in J \tag{8}$$

$0 - 1$ variables:

$$C_j \in \{0, 1\},\ \forall_j \in J \tag{9}$$

$$X_{ij} \in \{0, 1\},\ \forall_i \in I,\ j \in J \tag{10}$$

(2) Inequality constraints of charging station charger configuration

$$N_{\min} \leq N_j = N_{\max},\ j \in J \tag{11}$$

In formula 11, $N_{\min}$ and $N_{\max}$ are the maximum and minimum chargers configured at the charging station respectively.

(3) Inequality constraints of distance between charging stations

To ensure the charging station layout density is not too large, the distance between stations is constrained as follows:

$$\lambda D_{jj'} \geq D_{\min},\ j,\ j' \in J;\ j \neq j' \tag{12}$$

In formula 12, $D_{jj'}$ is the distance between charging station j and j'; and D_{min} is the minimum distance between charging stations.

(4) Inequality constraints of the distance between charging demand points and charging stations

To avoid the need for EV users to drive a long distance to a charging station, the distance constraint from charging demand point to charging station is:

$$X_{ij} d_{ij} \leq d_{\max},\ \forall_i \in I,\ j \in J \tag{13}$$

In formula 13, $d_{\max}$ is the maximum distance that the user can travel to charge their car battery.

4. ALGORITHMS DESIGN

4.1 Introduction to Improved Evolutionary Algorithms

The improved evolutionary algorithms enhance the fitness allocation mechanism and introduce the concept of the minimum neighbor density estimation mechanism [iii]. A more accurate guidance in the search process improves the diversity of the population and preserves the marginal individuals of the optimal front end of Pareto. With fewer parameter settings, a fast convergence speed and a strong searching ability, the distribution of the Pareto optimal solution obtained is uniform. When there are more objective functions, the convergence of the bounds can still be made in the direction of the optimal Pareto front end.

4.2 The Process of Improved Evolutionary Algorithms

The process of improved evolutionary algorithms is as follows:

(0) Generates an initial population P_0 and an empty external file A_0, setting $t = 0$.

(1) The fitness values of individuals in population P_t and external archive A_t are calculated.

(2) Determine $P_0 = \{x^i | x^i \in P_t \cup A_t \text{ Not bad}\}$, if A_{t+1} is larger than $\overline{N}$, then trim A_{t+1}; if the size of A_{t+1} is less than $\overline{N}$, then the dominated solution of P_t and A_t is added to A_{t+1} until its size is equal to $\overline{N}$.

(3) If $t > T$, then output the external file A_{t+1} and stop searching.

(4) For external file A_{t+1}, select individuals in the mating pool using the binary tournament method with substitution.

(5) Cross and mutate the mating pool and population P_{t+1}, $t = t + 1$, and go to step (2).

The process of improved evolutionary algorithms is shown in Figure 1:

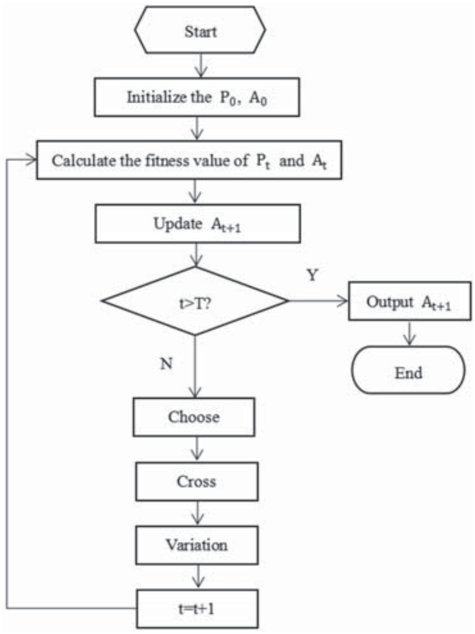

Figure 1 The process of improved evolutionary algorithms.

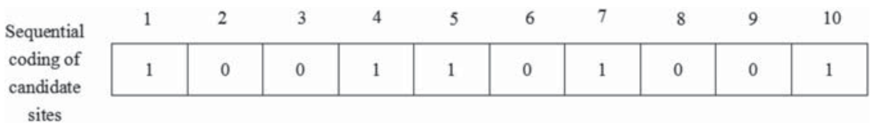

Figure 2 Examples of feasible solutions of the first layer coding.

4.3 Optimization of Improved Evolutionary Algorithms

There are two decision variables in this model: whether to build a station at candidate station j, whether to build the site scale C_j at candidate point j. There is also an intermediate variable: whether demand point i to candidate point j accepts service X_{ij}. Aiming at the particularity of the problem of charging station location and capacity, the specific implementation method of the algorithm is given.

(1) Chromosome coding.

Chromosomes are encoded in a two-layer structure. The first layer encodes whether the candidate stations have established charging stations. A fixed number of stations to be built are selected from a certain number of candidate stations after inspection from various aspects and binary coding is adopted. According to:

$$C_j = \begin{cases} 0, \text{Establish a charging station at} \\ \quad \text{candidate station } j \\ 1, \text{No charging station is established at} \\ \quad \text{candidate station } j \end{cases}$$

then the coding length of the first layer is the number of candidate stations J, the element 1 in the code represents the establishment of a charging station and the number of 1 is M (the number of charging stations to be built). The other elements are 0 for no charging station. For example, select 5 stations to be built from 10 candidate stations. Examples of feasible solutions of the first layer coding are shown in Figure 2:

The first layer codes the construction location of the charging station and the second layer codes the scale of the station to be built. The second layer of coding corresponds in turn to the construction scale in which the element in the first layer of coding is 1(i.e. the station to be built). Since N_j is an integer variable, binary coding is still used when coding the size of the station.

(2) Design idea of the genetic operation

① Choose a strategy. The proportional selection operator is adopted here, which means that the probability of an individual being selected and copied to the next generation is positively correlated with its fitness value. Roulette wheel selection is usually adopted, which is based on the principle that the probability of an individual being selected is based on the relative fitness of the individual.

② Cross-operator design. To effectively solve the legality and validity of the new solution after the coding crossover designed in this paper, the design idea of the crossover operator in this paper is as follows: first, the first layer of coding is crossed, and then the second layer of coding is crossed. The second layer conducts the crossover operation on the scale of each station to be built to realize that each station size to be built has the opportunity to obtain crossover operation. A single point crossing method is used to cross layers. A multi-level coding cross-operation flow chart is shown in Figure 3:

③ Mutation operator design. First, the mutation condition must be satisfied. If it is satisfied, the chromosome

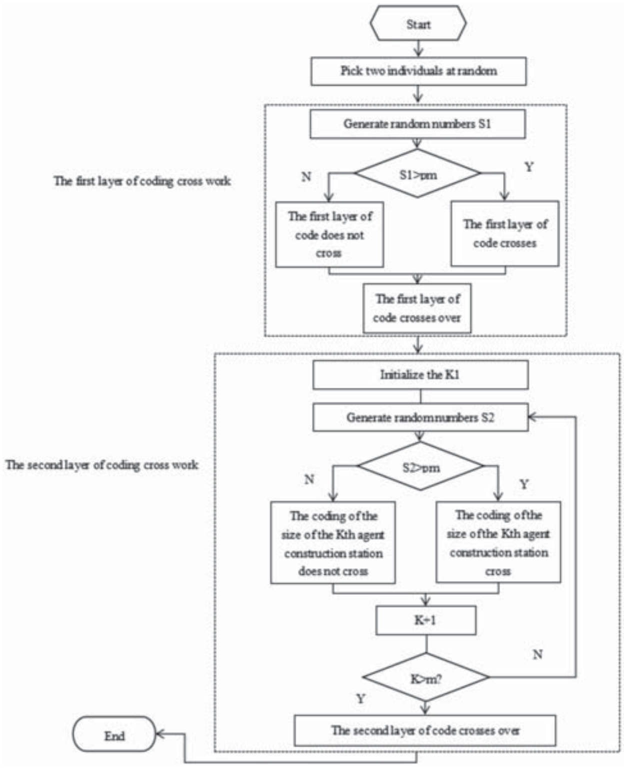

Figure 3 Multi-level coding cross-operation flow chart.

mutation will be achieved. Discontent stays the same. If the mutation condition is satisfied, a decision is again made as to whether to carry out the mutation in the first layer or the second layer. If the second layer of coding varies, but also a decision must also be made as to which station to build the scale of the station variation.

(3) Fitness evaluation

Calculate the three index values corresponding to individual i in the population and the external file and give i an intensity value $S(i)$, denoting the number of solutions dominated by the individual.

$$S(i) = \left|\left\{x^j \in P_t + A_t, x^i \sim x^j\right\}\right| \tag{14}$$

On the basis of $S(i)$, the original fitness value $R(i)$ of individual i is equal to the sum of the strength values of all the individuals that dominate the individual:

$$R(i) = \sum_{x^j \in P_t + A_t, x^i \sim x^j} S(j) \tag{15}$$

In the calculation of $R(i)$, both the population and the individuals in the external archive are taken into account, and the smaller the original fitness value, the fewer individuals dominate the individual. $R(i) = 0$ means that individual i is non-cleaved. The density $D(i)$ of the individual was calculated by using the k-nearest neighbor method.

$$D(i) = \frac{1}{\sigma_i^k + 2} \tag{16}$$

where σ_i^k is the distance between individual i and the k-nearest neighbor in the target space, $k = \sqrt{N + \overline{N}}$.

Finally, the fitness value $F(i)$ of individual i is the sum of the original fitness value and the density value:

$$F(i) = R(i) + D(i) \tag{17}$$

(4) Performance evaluation of the design algorithm

Because of its inherent parallelism, the evolutionary algorithm has the potential to find multiple optimal solutions in a single simulation run. However, in more complex applications, it is difficult for evolutionary algorithms to generate non-cracking, let alone the entire non-cracking set. Minimizing the distance between the resulting non-cracking front and the optimized front is one of the performance indicators of multi-objective optimization. The distance between the obtained non-cracking front and the optimal solution front is taken as the criterion to evaluate the algorithm performance.

The non-inferior solution set $A \in X_P$ and the distance formula are given and a function is introduced to evaluate the quality of the relevant decision space. The function gives the distance to the optimal solution set:

$$M(A) := \frac{1}{|A|} \sum_{a \in E} min \left|\left\{|a - x| x \in X_p\right\}\right| \tag{18}$$

5. NUMERICAL EXAMPLE

5.1 Example Description

To verify the effectiveness of the model and algorithm proposed in this paper, a case study on the location and capacity of charging stations is analyzed. The development area is 10.5km^2, divided into 30 functional areas, mainly

Table 1 The positions of demand points and the corresponding demands.

Number	X	Y	Demand	Number	X	Y	Demand
1	11.68	8.56	36	16	11.05	3.86	43
2	5.67	5.26	49	17	5.05	8.14	50
3	1.45	12.03	35	18	12.14	11.28	41
4	2.08	1.47	41	19	5.64	1.39	29
5	11.67	8.54	38	20	6.89	1.39	42
6	12.25	9.26	55	21	6.14	8.54	37
7	12.33	2.04	39	22	7.53	9.64	33
8	6.27	3.28	45	23	10.89	5.56	45
9	6.22	11.75	53	24	2.35	6.38	42
10	7.75	2.08	51	25	10.48	8.01	40
11	12.59	9.35	36	26	1.58	6.48	37
12	11.85	4.29	55	27	7.35	10.25	40
13	10.73	7.05	58	28	2.17	1.05	39
14	12.15	2.25	47	29	1.86	4.78	42
15	3.17	8.04	45	30	6.54	10.75	46

Table 2 The location of the candidate stations.

Number	X	Y	Number	X	Y
1	6.22	11.75	9	10.48	8.01
2	11.85	4.29	10	10.89	5.56
3	10.73	7.05	11	7.53	9.64
4	11.67	8.54	12	11.05	3.86
5	12.25	9.26	13	12.14	11.28
6	11.68	8.56	14	6.54	10.75
7	3.17	8.04	15	7.35	10.25
8	12.15	2.25			

residential, commercial, office and so on and it is roughly divided into 30 charging demand points. Combined with the research practice, the site is to be selected from the 15 candidate charging stations that meet the requirements of station construction. The purpose of site selection is to select 8 stations for the construction of charging stations from the 15 candidate points. The number of electric vehicles at each charging demand point is related to the regional economic development and residents' consumption level. The data is investigated and the charging demand of each demand point is calculated. The positions of the demand points and the corresponding demands are shown in Table 1:

The location of the candidate stations is shown in Table 2:

5.2 Parameter Settings

The binomial model of the number of chargers N_j for fixed investment in charging stations is as follows:

$$T(N_j) = W + qN_j + eN_j^2 \tag{19}$$

The binomial model of the number of chargers W for fixed investment in charging stations is as follows: W is 1 million yuan; q is the investment related to the unit price of the charger, which is set as RMB 50,000 per unit; e is the equivalent investment coefficient related to the number of chargers, including land acquisition costs and supporting facilities, etc., which is set as RMB 20,000 per charger.

Annual operating expenses $Y(N_j)$ are set at 10% of fixed investment costs; the depreciation life of the charging station is n_{year}; r_0 is 0.08. The charging cost per unit distance on the way to charging is 8 yuan/km. The non-linear coefficient of urban roads is 1.2. At present, the average price of quick charging for an electric vehicle is 4 yuan per vehicle; the proportion of the number of vehicles in non-vacant period service to the number of vehicles in full day service is 0.9; the duration of the non-vacancy period is 16 hours; hence, it is possible for vehicles to recharge their batteries in minutes assuming that the average service time of the charger is 15 minutes.

The maximum and minimum chargers in the charging station are $N_{\max}$ and $N_{\min}$ respectively; the minimum distance between charging stations is 0.5km; and users can drive up to 2km to recharge their batteries.

5.3 Example Solution

Based on the improved evolutionary algorithms, the example solution is as follows:

(1) Optimize parameter settings

After the parameter analysis, the operating parameters of the algorithm are determined as follows: the maximum number of iterations is 150, the internal and external population sizes are 200 and 20 respectively, the crossover probability is 0.6, and the mutation probability is 0.08.

(2) Analysis of the optimization results

Table 3 Indicators of the calculation example.

Independent operation	1	2	3	4	5	6	7	8	9	10
Indicator M	5.867	4.814	10.238	0.456	1.928	7.246	15.459	7.762	19.577	2.054
Independent operation	11	12	13	14	15	16	17	18	19	20
Indicator M	12.057	0.046	0.356	17.758	6.647	13.145	10.258	10.689	7.856	0.086

Table 4 Comparison table of optimization results.

Projects	Scheme 1	Scheme 2	Scheme 3	Scheme 4
Site and corresponding size (serial number of agent construction station and corresponding number of charging machines)	[4,4]	[4,3]	[4,2]	[1,4]
	[5,2]	[5,3]	[5,3]	[2,4]
	[5,3]	[5,4]	[5,3]	[6,3]
	[7,4]	[7,3]	[7,3]	[9,4]
	[13,3]	[13,2]	[13,2]	[10,3]
	[15,3]	[15,2]	[15,2]	[11,10]
	[16,4]	[16,3]	[16,3]	[12,4]
	[20,3]	[20,2]	[20,4]	[17,3]
1.Economic index	1442.99587	1442.19028	1415.13284	2030.38954
2.The average utilization index of the charger	1.00028	1.00182	1.56954	9.85641
3. .User's charging convenience index		1.52589	1.52911	2.39674

The example was run independently for 20 times and all the optimization results were statistically analyzed to obtain the complete front of the example. Then the example was run again 20 times independently, and the distance index between the non-cracking front and the complete front solution after each run was calculated. The range of the index is below 20, that is, the average distance between the non-cracking solution set and the real optimal solution set obtained by each independent operation is below 20. Compared with the optimized results, the relative proportion is very small, that is, the non-inferior solutions obtained by each simulation are close to the real frontier and are relatively stable. This shows that the parameter settings of the design and algorithm are reasonable and the independent simulation can give a more stable optimization solution. Indicators of the calculation example are shown in Table 3:

The number of frontiers in this paper is 20, so there are 20 multi-objective and dual-objective optimization schemes for the location and capacity of charging stations. A comparison table of the optimization results of four of the schemes is shown in Table 4:

It can be seen from Table 4 that the dual-objective optimization scheme 1 obtains good results on both index 1 and index 2, but ignores the effect of index 3. In practice, the index is an important factor in the growing popularity of electric vehicles. Therefore, it is of practical significance to take the user's charging convenience as the third index. Multi-objective optimization scheme 2 is a compromise solution in three indicators, that is, economy, users and resource utilization (the average utilization rate of the charger) all reach an equilibrium state; scheme 3 can achieve good results in the index, but at the cost of index 2; scheme 4 achieves the best results on metric 2 but sacrifices metric 1 and metric 3 to achieve this. The decision maker can choose the final compromise solution or the optimal solution from the obtained non-cracking according to the overall strategy of the charging station (the preference of the decision maker is whether the economy is the priority or the utilization rate of the charging machine or the charging convenience of the user).

Improved evolutionary algorithms are a very effective method in multi-objective decision analysis. The basic processing idea is as follows: first, determine the initial decision matrix, then normalize the initial matrix, and find the optimal and worst scheme from the priority schemes. Then, the distance between each evaluation object and the optimal scheme and the worst plan is calculated respectively to obtain the relative proximity of each evaluation scheme. After sorting, the pros and cons of the scheme are evaluated based on this.

6. CONCLUSION

In recent years, countries around the world have developed electric vehicles as an important strategy for national energy security and transformation to a low carbon economy. With the maturity of electric vehicle technology, China is about to enter a period of vigorous development of electric vehicles. Charging facility planning is a key factor affecting the development of electric vehicles, which is related to whether the charging network can be formed. Therefore, it is of theoretical and practical significance to study the layout of charging facilities. By comprehensively considering the various influencing factors of charging stations, a multi-objective planning model for electric vehicle charging stations was established by constructing three indicators, namely economy, average utilization rate of charging stations and user charging convenience, to achieve a balance between the three indicators. This improves the scientific nature of the planning scheme and the efficiency of the planning, and makes the location and capacity of the charging station more reasonable. The improved evolutionary algorithm method is designed to solve the model.

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