Research on Optimizing the Location and Capacity of Electric Vehicle Charging Stations

Lingling Yang[1], Jiali Chen[1], Wenzao Li[1,2](✉), and Zhan Wen[1]

[1] College of Communication Engineering, Chengdu University of Information Technology, Chengdu, China
yanglledu@sina.com, lwz@cuit.edu.cn

[2] School of Computing Science, Simon Fraser University, Burnaby, Canada

Abstract. Charging stations deployment is an important problem in Electric Vehicle (EV) networks. The distribution of EV is complicated in urban environments. Therefore, reasonable location deployment will avail to reduce construction costs and improve user experience. Aim to this, this paper comprehensively considers the cost of charging stations and the charging costs of EVs. Studied the charging station location, charging station capacity and the optimization algorithms for charging station location, and proposed a method for estimating the optimal location and optimal capacity allocation of EV charging stations. Firstly, this paper uses the Voronoi diagram to divide the service range of the charging stations, then uses the differential evolution algorithm combined with the particle swarm optimization algorithm (DEIPSO) to solve the charging station location model, and finally consider the residence time of EV in the charging station, use queuing theory to solve the charging station capacity allocation model. The experimental results shows that DEIPSO can better jump out of the local optimum and achieve the global optimum; the proposed model can plan the charging station on the basis of fully considering the total charging costs of charging stations and EVs.

Keywords: EV · Charging stations · Location · Capacity allocation · DEIPSO algorithm

1 Introduction

1.1 Background and Motivation

At present, the related research of EV charging stations at home and abroad mainly focuses on the following aspects: (1) Research on Location Model of Charging Station. Mehmet, C.C. et al. [1] believe that the optimal deployment location of the charging station is closely related to the number of EVs and traffic density in the planning area, and propose to use data mining methods to estimate the optimal location of the charging station; Johannes, S. et al. [2] solve the problem of user's charging difficulties, considering the user's charging habits and propose a method for selecting the location of the charging

X. Wu et al. (Eds.): QShine 2020, LNICST 381, pp. 76–90, 2021.
https://doi.org/10.1007/978-3-030-77569-8_6

station; Bi, R. et al. [3] considered the influence of different vehicle owners' charging behavior and established multiple models for comparative analysis. The results showed that the vehicle owners' charging behavior will have a greater impact on the simulation results, so on this basis, optimize the location of the charging station; Phonrattanasak, P. [4] under the constraints of the distribution network and traffic restrictions, the planning model of charging station is established by considering the total cost of fast charging station and the total loss of distribution network. (2) Research on the charging station capacity allocation model. To meet the charging needs of EVs, the vehicles do not consider the problem of waiting in line when charging. Some research scholars determine the number of chargers in charging stations by calculating the maximum charging demand within the service range of charging stations [5–7]; by considering the queuing problem of EVs during charging, some researchers have proposed to use the method of queuing theory [8–10] to establish the capacity allocation model of charging stations. (3) Research on the algorithm for solving the location model. Mehar, S. et al. [11] added a new operator to the traditional genetic algorithm to estimate the optimal location of the charging station. The improved genetic algorithm can prevent the algorithm from prematurely converging and improve the efficiency of the algorithm; Han, F.J. [12] combined Voronoi diagram with traditional particle swarm optimization algorithm to improve the optimization effect and optimization speed of the algorithm; because the traditional particle swarm optimization algorithm is easy to fall into the local optimum, some scholars [5, 6, 13] combined Voronoi diagram with improved particle swarm optimization algorithm to further improve the optimization speed of the algorithm.

1.2 Challenges and Our Solution

EVs have become an important part of the new energy development strategy, and is the development direction of new energy vehicles. The construction of EV charging stations is a prerequisite for the development and popularization of EVs. Due to the relatively high construction cost of charging stations and the large amount of land and power resources they occupy, the development of charging stations is relatively slow. The layout of the charging stations that have been constructed is unreasonable in space and has a great blindness. The unreasonable deployment of charging stations will affect the urban transportation network planning, increase the driving costs of vehicles, and make it difficult for operators to make profits or even lose money. Whether the planning of EV charging stations is reasonable will directly affect the number of EVs used and the improvement of service levels.

The above literature has important guiding significance for the planning of charging stations, but them ignores that the location of EV charging stations will affect many aspects, which in turn will not be conducive to the development of charging stations, and different location optimization algorithms solving the location problem of the charging station is also a key part, the quality of the selection algorithm is directly related to the accuracy of the final optimization result. Therefore, in the location and capacity model of the charging station, this paper comprehensively considers the actual influencing factors in real life, and considers the number of EVs, the charging behavior of users, the cost of building stations and operating costs of charging stations in different regions, and proposed the location and volume model of EVs charging station. On the basis of the traditional particle swarm optimization algorithm is easy to fall into the local optimal, proposing a differential evolution particle swarm optimization algorithm (DEIPSO) to verify the feasibility of the model.

1.3 Paper Structure

The rest of the paper is organized as follows: Sect. 2 introduces the prediction model of EV charging demand points in the planning area. Section 3 introduces the mathematical model of EV charging station location. Section 4 introduces the mathematical model of EV charging station capacity allocation and objective function. Section 5 introduces the constraints in this model. Section 6 introduces the DEIPSO algorithm. Section 7 introduces the simulation scenarios of the experiment in this paper. Section 8 introduces the simulation results of the model in this paper. Section 9 summarizes the paper.

2 Division of Charging Demand Points

Charging demand is the number of EVs that need to go to the charging station for charging in a certain area and time. The charging demand is closely related to the traffic density. In areas with charging demand, the traffic density near the area will also increase. Therefore, the service capacity of the charging station should match the traffic density of the corresponding area to meet the charging needs of EVs as much as possible. EVs are located in most areas of the city, and vehicles will go to the nearest charging station to charge without the guidance of charging. Therefore, in this paper, the planning area is divided into several smaller areas [14], and each small area is a charging demand cell. Nie, Y. et al. [15] proposed that in any area, traffic flow is conserved for a period of time. According to this conclusion, it can be assumed that the number of EVs in each small area remains unchanged, so for the convenience of calculation, the geometric center of each cell is regarded as a charging load point, according to the number of EVs at each charging load point, calculating the charging demand of each cell.

3 Mathematical Model of EV Charging Station Location

The construction of the charging station not only needs to consider the construction cost of the charging station, but also needs to consider the driving cost of EVs. This paper mainly considers the fixed construction cost of the charging station, the annual operating cost and the charging satisfaction of EV users, and establishes a mathematical model for the location of EV charging stations, as shown in Eq. (1).

$$TotalCost = CSC + \frac{1}{\varphi\left(v_j, d_{ij}\right)} \tag{1}$$

In Eq. (1), *TotalCost* is the total cost; *CSC* is the construction cost of the charging station; $\varphi(v_j, d_{ij})$ is the EV user satisfaction.

The construction cost of the charging station is composed of the fixed construction cost and the annual operating cost of the charging station, as shown in Eq. (2).

$$CSC = \sum\nolimits_{i \in CS} f_{cs}(N_i) R_Z + u_{cs}(N_i) \tag{2}$$

The fixed construction cost f_{cs} of the charging station is shown in Eq. (3).

$$f_{cs}(N_i) = W_i + q_i N_i + m_i \tag{3}$$

In Eq. (3), W_i is the fixed investment cost of each charging station; q_i is the construction investment cost related to the charger in the charging station; m_i is the investment cost related to the transformer in the charging station; N_i is the number of charging piles in charging station i.

By reading a large number of references and combining the simulation environment of this paper, the annual operating cost of the charging station is shown in Eq. (4).

$$u_{cs}(N_i) = 0.1 f_{cs}(N_i) \tag{4}$$

R_Z is the discount factor of the charging station as shown in Eq. (5).

$$R_Z = \frac{\left(rr(1 + rr)^{ms}\right)}{(1 + rr)^{ms-1}} \tag{5}$$

In Eq. (5), rr is the discount rate and ms is the depreciation period of the charging station.

EV user satisfaction: EV user satisfaction indicates the evaluation of the charging station by the EV users at the charging station, as shown in Eq. (6).

$$\varphi\left(v_j, d_{ij}\right) = \frac{1}{VTC + VTE + CSL} \tag{6}$$

In Eq. (6), VTC is the cost of the travel time for EVs to reach the charging station; VTE is the cost of energy consumption for EVs to reach the charging station; CSL is the cost of waiting time for EVs at charging station, and the size of the function value indicates the satisfaction of the EV user with the charging station.

In this paper, consider the non-linear coefficient of urban roads to calculate the distance traveled by EVs, as shown in Eq. (7).

$$D_{ij} = \lambda_{ij} * \gamma_{ij} * d_{ij} \tag{7}$$

In Eq. (7), λ_{ij} is the non-linear coefficient of the urban road from the demand point j to the charging station i; γ_{ij} is the reentry coefficient of the EV journey from the demand point j to the charging station i; d_{ij} is the linear distance from the demand point j to the charging station i.

$$\lambda_{ij} = \frac{d_{tij}}{d_{ij}} \tag{8}$$

The minimum value of λ_{ij} is 1, and the smaller the λ_{ij}, the more convenient the traffic between the two points.

The time-consuming cost of an EVs in road is shown in Eq. (9).

$$VTC = \frac{365\beta_{time}N_c\left(\sum_{i\in CS}\sum_{j\in J_{CD}} pn_jD_{ij}\right)}{v_j} \tag{9}$$

In Eq. (9), β_{time} is the time cost of EVs; p is the daily fast charging probability of EVs; n_j is the number of EVs at demand point j; v_j is the average driving speed of EVs; N_c is the number of daily charging of EVs, as shown in Eq. (10).

$$N_{\mathrm{c}} = \frac{E_{1km} * k}{\text{battery}} \tag{10}$$

In Eq. (10), E_{1km} is the energy consumption of EVs; k is the daily mileage of EVs; *battery* is the battery capacity of EVs.

The cost of energy consumption for EVs to reach the charging station is shown in Eq. (11).

$$VTE = 365mN_c\left(\sum_{i\in CS}\sum_{j\in CD} n_jD_{ij}E_{1km}\right) \tag{11}$$

In Eq. (11), m is the electricity price in the planned area.

4 Mathematical Model of EV Charging Station Capacity Allocation

When an EV is charging at a charging station, if the charging station does not have an idle charging pile, it needs to wait in line for service. Queuing theory is through statistical research on the arrival and service time of service objects, to obtain statistical laws of quantitative indicators such as waiting time, queue length, and length of busy period, and then to improve the structure of the service system or reorganize the service objects according to these laws. So that the service system can meet the needs of the service target, but also can make the organization's expenses the most economical or some indicators are optimal. The planning of the number of charging piles for EV charging stations is to meet the charging needs of EVs and to optimize the economics of the charging station. Therefore, this paper uses the queuing theory multi-service desk model (M/M/S) to establish charging stations capacity allocation model. In the queuing system of the charging station, the arrival time of EVs follows the negative exponential distribution with the parameter λ, and the service time of each service desk is independent of each other, with the negative exponential distribution with the parameter μ. The average queue length L_s of the EV at the charging station is shown in Eq. (12).

$$L_s = \frac{P_0\rho^{N_i}\rho_{N_i}}{N_i!\left(1-\rho_{N_i}\right)^2} + \rho \tag{12}$$

In Eq. (12), P_0 is the probability that all charging piles in the charging station are idle, as shown in Eq. (13).

$$P_0 = \left[\sum_{n=0}^{N_i-1}\frac{\rho^n}{n!} + \frac{\rho^{N_i}}{N_i!\left(1-\rho_{N_i}\right)}\right]^{-1} \tag{13}$$

In Eq. (13), n is the number of EVs.

$$\rho_{N_i} = \frac{\rho}{N_i} = \frac{\lambda}{N_i \mu} \tag{14}$$

The residence time of the EV at the charging station is shown in Eq. (15).

$$W_s = \frac{L_s}{\lambda} \tag{15}$$

The cost of the waiting time of an EV at a charging station is shown in Eq. (16).

$$CSL = 365\beta_{time}N_c\left(\sum\nolimits_{i\in CS}\sum\nolimits_{j\in CD} n_j\left(W_s - \frac{1}{\mu}\right)\right) \tag{16}$$

The objective function of this paper is shown in Eq. (17).

$$Cost = min(TotalCost) \tag{17}$$

In Eq. 17, Cost is the lowest cost considering the cost of the charging station (construction cost, annual operating cost) and the cost of the EV (road travel time cost, energy consumption cost, waiting time cost at charging station).

5 Model Constraints

The number of charging piles in each charging station is constrained by Eq. (18).

$$N_{i,min} \le N_i \le N_{i,max} \tag{18}$$

In Eq. (18), $N_{i,min}$ is the minimum number of charging piles included in the charging station; $N_{i,max}$ is the maximum number of charging piles included in the charging station.

The distance constraint between charging stations is shown in Eq. (19).

$$D_{min} \le D_{ij} \le 2 * D_{min} \tag{19}$$

In Eq. (19), D_{min} is the minimum distance between two charging stations.

The distance constraint from the charging demand point to the charging station is shown in Eq. (20).

$$max\left(D_{ij}\right) \le D_{max} \tag{20}$$

In Eq. (20), D_{max} is the maximum service radius of the charging station.

In order to avoid the long queue of EVs at the charging station and ensure the stability of the queuing system, the arrival rate of EVs must be less than the product of the service rate of the charging station and the number of charging piles, as shown in Eq. (21).

$$\lambda \le \mu N_i \tag{21}$$

The residence time limit of EVs at charging stations is shown in Eq. (22).

$$W_{\mathrm{s}} \le W_{s-max} \tag{22}$$

In Eq. (22), W_{s-max} is the maximum residence time of the EV at the charging station ($W_{s-max} = 40$ min).

6 Location Algorithm Analysis

6.1 Voronoi Diagram

Voronoi diagram is composed of a set of continuous polygons formed by a set of vertical bisectors connecting two adjacent points. In the Voronoi diagram, the distance from any point within a polygon to the control points that constitute the polygon is less than the distance to the control points of other polygons. In this paper, assuming that the coordinates of the charging station are control points, using these control points to draw a Voronoi diagram, the service area of the charging station can be divided.

6.2 Improve Particle Swarm Optimization

The particle swarm optimization searches the search space in parallel through a group of initialized groups, and realizes the evolution of the population through the competition and cooperation between individuals in the population. Fewer parameters need to be set, and the operation is simple.

In particle swarm optimization, each particle represents a potential solution to the problem, and the fitness of the particle is judged by the fitness function. The initial value of the particle swarm is a group of random particles, and the optimal solution is found according to the iteration. In each iteration, the particle updates its position and velocity according to the individual optimal value and the global optimal value. The particle velocity update formula is shown in Eq. (23).

$$V_t = \omega * V_t + c_1 r_1 (P_{best} - x_t) + c_2 r_2 (g_{best} - x_t) \tag{23}$$

In Eq. (23), ω is the inertial weight; c_1 c_2 is the learning factor; r_1 r_2 is the random number in the range [0,1]; P_{best} is the individual optimal value of the particle; g_{best} is the global optimal value of the particle. The speed update formula consists of 3 parts, $\omega * V_t$ is the inertial part, the motion inertia of the reaction particle; $c_1 r_1 (P_{best} - x_t)$ is the cognitive part, and the reaction particle has a tendency to update its own history optimally; $c_2 r_2 (g_{best} - x_t)$ is the social part, and the reaction particle has a tendency to update the historical optimal value in the directed group.

When the learning factor c_1 is greater than c_2, particles pay attention to their historical position; when c_1 is less than c_2, particles pay more attention to social information. We can find that in the early stage of the particle movement, the particle needs to update to its historical optimal value; in the later stage of the movement, the particle needs to pay more attention to update to the group optimal value. Therefore, in this paper, the improved particle swarm algorithm (IPSO) is used. In IPSO, asymmetric arccosine strategy is used to set the learning factor, as shown in Eqs. (24) and (25).

$$c_1 = c_{1end} + (c_{1start} - c_{1end}) * (1 - \mathrm{acos}(-2^*\mathrm{n}/(\mathrm{N}+1) + 1)/\pi) \tag{24}$$

$$\mathrm{c}_2 = \mathrm{c}_{2\mathrm{end}} + (\mathrm{c}_{2\mathrm{start}} - \mathrm{c}_{2\mathrm{end}}) * (1 - \mathrm{acos}(-2^*\mathrm{n}/(\mathrm{N}+1) + 1)/\pi) \tag{25}$$

In Eq. (24) and (25), $c_{1start} = 2.75$, $c_{1end} = 0.5$, $c_{2start} = 1.25$, $c_{2end} = 2.25$.

Equation (26) shows the particle position update formula.

$$X_t = X_t + V_t \tag{26}$$

In this paper, the particle out-of-bounds problem is solved by restricting the particle's active area. The particle's active area *Particle_Area* is shown in Eq. (27).

$$Particle\_Area \in \left[x_{min}, x_{max}\right] \cup \left[y_{min}, y_{max}\right] \tag{27}$$

In Eq. (27), $x_{min}, x_{max}, y_{min}, y_{max}$ are the smallest horizontal axis coordinate point, the largest horizontal axis coordinate point, the smallest vertical axis coordinate point, and the largest vertical axis coordinate point in the simulation environment.

6.3 Differential Evolution Algorithm

Differential evolution (DE) algorithm is a group-based adaptive global optimization algorithm. The core part of the algorithm includes mutation, hybridization and selection operations. The mutation operation of the differential evolution algorithm is shown in Eq. (28).

$$V_{di} = X_{dr1} + F_0(X_{dr2} - X_{dr3}) \tag{28}$$

In Eq. (28), X_d is the initial population; $\mathrm{r}_1 r_2 r_3$ is a random value ($\mathrm{r}_1 r_2 r_3 \epsilon [1, N]$), and $\mathrm{r}_1 \neq r_2 \neq r_3 \neq i$; N is the population size. The hybridization operation is shown in Eq. (29).

$$U_{dij} = \begin{cases} V_{dij} rand \le CR \, or \, randi(1, Tn) = j \\ X_{dij} rand > CR \, or \, randi(1, Tn) \neq j \end{cases} \tag{29}$$

In Eq. (29), CR is the mutation probability, $j \in [1, Tn]$. The selection operation is shown in Eq. (30).

$$X_d = \begin{cases} U_d \, fit(U_d) < fit(X_d) \\ X_d \, fit(U_d) \ge fit(X_d) \end{cases} \tag{30}$$

In Eq. (30), $fit(U_d)$ is the fitness of the population U_d; $fit(X_d)$ is the fitness of the population X_d.

6.4 Differential Evolution Improve Particle Swarm Optimization

In this paper, by combining DE algorithm and IPSO to improve the global optimization ability of the solution, the steps are as follows.

(1) According to the charging demand in the planning area and the service capacity of the charging station, estimate the number range of charging stations in the planning area $Tn \in [N_{min}, N_{max}]$.

(2) Use the DE algorithm to plan the charging station, set the range of the charging station site *CSposition*, $CSposition \in [x_{min}, x_{max}] \cup [y_{min}, y_{max}]$, and randomly generate the charging station site *Xd* within this range, $Xd = [(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)]$, N is the population size.

(3) Set the initial dimension of the DE algorithm, that is, the initial number of charging stations $Tn = N_{min}$.

(4) According to Eqs. (28), (29), and (30), mutation operation, hybridization operation, and selection operation are performed respectively. After each operation, a new charging station position must be generated reasonably according to the constraints.

(5) Set the maximum number of iterations of the algorithm. When the algorithm reaches the maximum number of iterations, the algorithm stops. At this time, the position set *DEX* of the charging station and the corresponding adaptation value *DEF* are counted.

(6) The IPSO is used to plan the charging station, the initial station site range is *CSposition*, and the initial charging station site is X, $X = X_d$.

(7) Set the initial dimension of the IPSO, that is, the number of charging stations $Tn = N_{min}$.

(8) Calculate the local optimal solution and the global optimal solution, update the particle speed according to Eq. (23), and update the particle position according to Eq. (26), and calculate the local optimal solution and global optimal solution of the updated population.

(9) Set the maximum number of iterations of the algorithm. When the algorithm reaches the maximum number of iterations, the algorithm stops. At this time, the charging station position set *IPSOX* and the corresponding adaptation value *IPSOF* are counted.

(10) Combining *DEF* and *IPSOF* to obtain a new fitness value combination *NewFit*, $NewFit = [DEF, IPSOF]$, the dimension of *NewFit* is $2N$.

(11) Sort *NewFit* in ascending order to obtain the new population's fitness value *NewF*, and take the first N fitness values for the charging station location *NewP*.

(12) Using *NewP* as the initial site, repeat steps (7), (8), (9). Obtain the charging station location set *IPSOX* and the corresponding fitness value *IPSOF*. By selecting the minimum value of *IPSOF*, the minimum total cost and the optimal deployment position of the charging station can be obtained.

(13) $Tn = Tn + 1$, repeat steps (4)–(12), until $Tn > N_{max}$, the algorithm stops.

(14) Count the total cost corresponding to the number of different charging stations, and select the number and location of charging stations corresponding to the optimal cost.

7 Simulation Scenario

The experiment process of this paper uses MATLAB software to simulate. In order to increase the scalability of the model, the algorithm realization module, environmental parameter module, and parameter calculation module are independently established in the program. This paper sets the simulation parameters based on the reference [14] simulation environment, as shown in Table 1.

Table 1. Simulation parameters.

Parameter	Value
Number of charging demand points (n)	34
Fixed investment (W_i)	2 millions
Investment-related to the unit price of the charging piles in the charging station (q)	0.35 millions
The investment cost related to the transformer in the charging station (e_i)	0.2 millions
Discount rate (rr)	0.08
Charging station depreciation period (ms)	20 years
Average driving speed of EVs (v)	30km/h
Non-linear coefficient of the urban road (λ_{ij})	1.2
Minimum number of charging piles in the charging station ($N_{i,min}$)	3
Maximum number of charging piles in the charging station ($N_{i,max}$)	30

Algorithm parameters settings are shown in Table 2.

Table 2. Algorithm parameters.

Parameter	Value
Number of particles (N)	20
Maximum number of iterations ($MaxIter$)	100
Inertial weights (W_s and W_e)	0.9 and 0.4
Scaling factor (F)	0.4
Mutation probability (CR)	0.6

The location of the charging demand points is shown in Fig. 1.

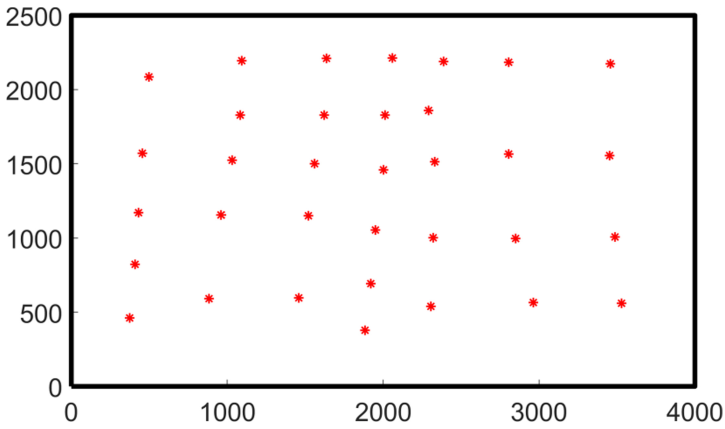

Fig. 1. Distribution of charging demand points

8 Simulation Results

The convergence curves of IPSO, DE, and DEIPSO are shown in Fig. 2.

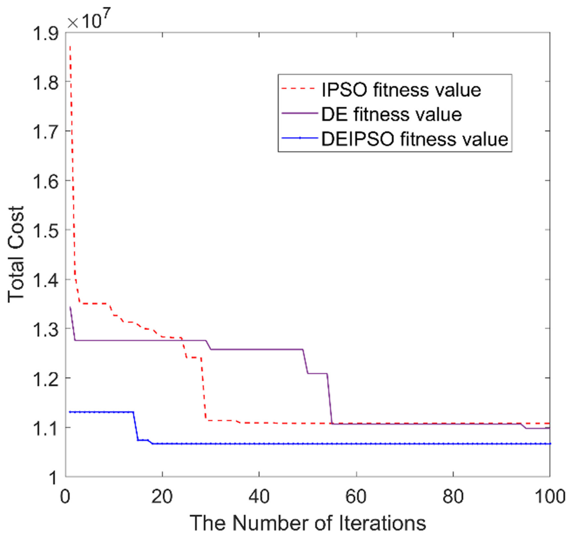

Fig. 2. Convergence curve

In Fig. 2, we can find that compared with IPSO and DE, DEIPSO can converge earlier and can jump out of the local optimum.

The changes in the cost of charging stations and the cost of driving EVs with the number of charging stations deployed are shown in Fig. 3.

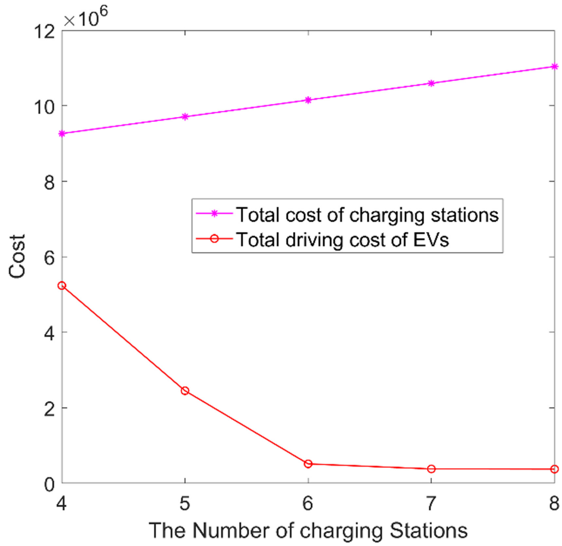

Fig. 3. Different costs vary with the number of charging stations deployed

In Fig. 3, we can find that as the charging station increases, the cost of the charging stations also increases, because the construction cost of the charging station is positively related to the number of charging stations deployed. The driving cost of EVs decreases as the number of charging stations increases, the reason is that as the number of charging stations increases, it will be easier for EVs to find the nearest charging station and reduce the distance traveled. Therefore, when selecting the number of charging stations to be deployed, it is necessary to comprehensively consider the cost of charging stations and the driving cost of EVs, as shown in Fig. 4.

In Fig. 4, We can find that when the cost of charging stations and the cost of EVs are considered comprehensively, the total cost of deploying six charging stations is the lowest. This is because when the number of charging stations is six, the total cost of charging station cost and EVs cost is the lowest.

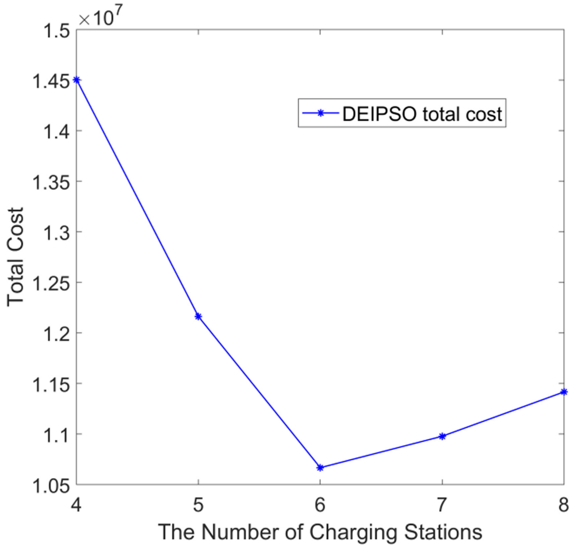

Fig. 4. The total cost varies with the number of charging stations deployed

The total cost of IPSO, DE, and DEIPSO changes with the number of charging stations deployed is shown in Table 3.

Table 3. Total cost changes.

Algorithm	IPSO	DE	DEIPSO
Total cost of deploying 4 charging stations (ten million)	1.5332	1.4833	1.4503
Total cost of deploying 5 charging stations (ten million)	1.2164	1.3645	1.2162
Total cost of deploying 6 charging stations (ten million)	1.2152	1.1311	1.0668
Total cost of deploying 7 charging stations (ten million)	1.1080	1.0979	1.0978
Total cost of deploying 8 charging stations (ten million)	1.4694	1.1501	1.1417

In Table 3, we can find that no matter how many charging stations are deployed, the total cost of using the DEIPSO algorithm is lower than the IPSO and DE algorithms. This is because the DE algorithm increases the diversity of the IPSO population and reduces the risk of falling into a local optimum.

The location distribution of charging stations in the planned area is shown in Fig. 5.

When six charging stations are deployed, the service indicators of the charging piles in the charging station are shown in Table 4.

In Table 4, we can find that the average residence time of EVs at the charging station is within 40min.

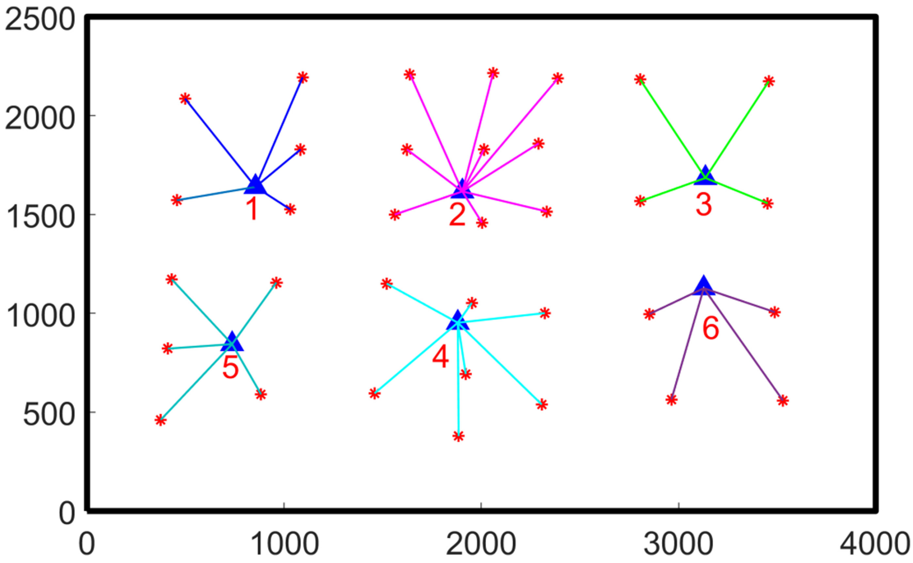

Fig. 5. Location of charging station deployment

Table 4. Service indicators of the charging piles in the charging station.

Charging station serial number	1	2	3	4	5	6
Number of charging piles	18	21	22	22	13	23
Residence time (min)	39.984	38.874	37.794	37.146	36.516	39.756

9 Conclusion

This paper comprehensively considers the cost of EVs charging and the cost of charging stations construction, and proposes a method of location and capacity for EV charging stations. The model of EV charging station location, the model of EV charging station capacity allocation, and the optimization algorithm of the location of the charging station are studied respectively. The DEIPSO algorithm is used to verify the feasibility of the site selection model for the site selection of charging stations; the queuing theory of this paper can be used to reasonably plan the number of piles in each charging station; by comparing the DE, IPSO, and DEIPSO algorithms, it is found that the DEIPSO algorithm can achieve a certain degree Jump out of the local optimal solution, finding the global optimal solution, and better deploy the charging station location.

Acknowledgement. This work supported by Sichuan Science and Technology Program 2019ZDZX0005.

References

1. Mehmet, C.C., Merve, Y., Arif, G., Hasan, K.: Estimation of optimal locations for electric vehicle charging stations. In: 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), Milan (2017)
2. Johannes, S., Matthias, E.: Finding suitable locations for charging stations-implementation of customers' preferences in an allocation problem. Int. Electric Veh. Conf. **12**, 17–19 (2014)
3. Bi, R., Xiao, J.J., Viswanathan, V., Knoll, A.: Influence of charging behaviour given charging station placement at existing petrol stations and residential car park locations in Singapore. Procedia Comput. Sci. **80**, 335–344 (2016)
4. Phonrattanasak, P.: Optimal placement of EV fast charging stations considering the impact on electrical distribution and traffic condition. In: 2014 International Conference and Utility Exhibition on Green Energy for Sustainable Development (ICUE). IEEE (2014)
5. Jiao, D.J., Su, X.L., Yan, X.X., Wang, W.C.: A location and capacity planning scheme for charging station based on Voronoi diagram and catfish particle swarm optimization algorithm. Autom. Technol. Appl. **37**(03), 5–10 (2018)
6. Ma, X.F., Wang, H., Li, Y., Wang, C., Hong, X.: Electric vehicle charging station planning based on variable weight Voronoi diagram and hybrid particle swarm optimization. J. Electrotech. **32**(19), 160–169 (2017)
7. Chen, J.P., Ai, Q., Xiao, F.: Electric vehicle charging station planning based on user travel needs. Electric Power Autom. Equipment **36**(06), 34–39 (2016)
8. Zheng, C.Q.: Research on the most optimal location of urban electric vehicle charging facilities. Nanchang University (2016)
9. Yang, H.M., Deng, Y.J., Qiu, J., Li, M., Lai, M.Y,. Dong, Z.Y.: Electric vehicle route selection and charging navigation strategy based on crowd sensing. IEEE Trans. Ind. Inform. (2017)
10. Jiao, D.J.: Research on the optimization of location and volume of electric vehicle charging stations. Shanxi University (2018)
11. Mehar, S., Senouci, S.M.: An optimization location scheme for electric charging stations. In: International Conference on Smart Communications in Network Technologies. Paris, France (2013)
12. Han, F.J.: Research on Optimizing the Location and Capacity of Electric Vehicle Charging Station. Nanchang University (2015)
13. Wang, H.: Research on optimal layout of electric vehicle charging stations based on hybrid discrete particle swarm optimization. North China Electric Power University (Beijing) (2017)
14. Liu, H.: Location and capacity optimization of electric vehicle charging stations based on particle swarm genetic hybrid algorithm. Xi'an University of Technology (2016)
15. Nie, Y., Ghamami, M.: A corridor-centric approach to planning electric vehicle charging infrastructure. Transp. Res. Part B **57**(57), 172–190 (2013)