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The location optimization of electric vehicle charging stations considering charging behavior

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Abstract
The electric vehicle is seen as an effective way to alleviate the current energy crisis and environmental problems. However, the lack of supporting charging facilities is still a bottleneck in the development of electric vehicles in the Chinese market. In this paper, the cloud model is used to first predict drivers' charging behavior. An optimization model of charging stations is proposed, which is based on waiting time. The target of this optimization model is to minimize the time cost to electric vehicle drivers. We use the SCE-UA algorithm to solve the optimization model. We apply our method to Dalian, China to optimize charging station locations. We also analyze the optimized result with or without behavior prediction, the optimized result of different numbers of electric vehicles, and the optimized result of different cost constraints. The analysis shows the feasibility and advantages of the charging station location optimization method proposed in this paper.

Keywords
Behavior prediction, cloud mode, optimization of charging station location, SCE-UA algorithm, waiting time

1. Introduction

In recent years, the electric vehicle (EV) has been seen as an effective way to alleviate the current resource crisis, energy crisis, and environmental problems due to its high efficiency, energy savings, low noise, and zero emissions. EVs have been widely promoted and used throughout the world, and are in line with China's current development ethos.

Many countries are actively promoting EVs by incentive policies and tax subsidies (such as no purchase tax, unlimited purchase number, and half parking fees, etc.). China is a populous country, but large resource consumption and energy issues have become bottlenecks restricting the rapid and healthy development of China. Because of the advantages of EVs, the Chinese government has made great efforts to promote their development by issuing preferential policies and lowering relevant consumption taxes.

However, the lack of charging stations has become a constraint on the development of new EVs. Compared with fuel vehicles, EVs are dependent on charging facilities. Users' travel decisions are very affected by the distribution of charging facilities. At present, some domestic and foreign parking lots have been built with a variety of charging equipment, such as charging piles. However, these charging facilities cannot meet the demand of EVs. Therefore, the construction of charging stations for the development of EVs cannot be ignored.

In recent years, research on the location problem of EV charging stations has attracted many scholars. He and colleagues[1] incorporated the local constraints of supply and demand on public EV charging stations into facility location models. This paper compared three classic facility location models—the set covering model, the maximal covering location model, and the p-median model—and showed that the p-median solutions are more effective than the other two models. Frade and colleagues[2] used a maximal covering model to optimize siting of public charging stations for Lisbon, Portugal. In this paper, nighttime demand and daytime demand were estimated separately to correspond to different residential and business uses. Xi and colleagues[3] developed a simulation-optimization model to determine the locations of slow chargers. These

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authors further explored interactions between the optimization criterion and the budget available. Cavadas and colleagues[4] split the day into time intervals to take into account the effects of peak hours. They consider the effect of demand transference. Results show that the method can greatly expand the satisfied coverage. Hiwatari and colleagues[5] analyzed the effective layout of charging stations based on the location of EVs running out of electricity in a road traffic simulator. Capar and colleagues[6] applied a flow-refueling location model to charging station problems under mild assumptions such as charging stations being incapacitated. The new formulation reduced the average solution time by over 70%. Cruz-Zambrano and colleagues[7] formulated two methods for locating fast-charging stations (maximizing service coverage and maximizing profit), and discussed the performance of the two proposed methods. Wang and colleagues[8] optimized the location of battery exchange stations to serve tourism transport for electric scooters. A battery exchanging scheme has rarely been put forward alone, and is often mentioned together with fast-charging technology. You and colleagues[9] proposed an O–D trip-based model which simultaneously determines the locations and types of recharging station and alternative-fuel vehicles (AFVs) recharging quantity at each recharging station. Chung and colleagues,[10] Nie and colleagues,[11] Sathaye and colleagues,[12] Dong and colleagues,[13] among others, proposed other methods for the problem.

Most studies about locating charging stations consider the distance between the demand point and the supply point. There are few studies that regard the waiting time for EVs to queue in charging station as a factor. Most researchers assume that EV drivers will choose the nearest charging station when they decide to charge. In the actual situation, the nearest charging station is not always the best choice. The charging time of EVs is long. It will take more than 20 min even in fast-charging mode. When there are a lot of EVs to be charged, the drivers need to wait in line. For the EV drivers, the time consumed by waiting for charging is more unbearable than the charging time. At this time, if drivers choose a charging station with a suboptimal distance, there will be little time to wait for charging. Then the total time cost will be less than the situation of choosing the nearest charging station. Therefore, the waiting time at the charging station should also be an important consideration when optimizing the charging station location.

The location of the charging station is designed to provide better service to EV drivers. And because of the importance of the waiting time at the charging station and long charging time, the EV driver will choose the best charging station for himself. Before optimizing the location of the charging station, the driver's choice behavior is predicted so that the charging station can provide better service for more drivers. Under different charging station location schemes, the driver's choice behavior will be different. Each charging station has a different number of customers at the same time, and the average waiting time at each charging station is different. So it is necessary to predict the driver's choice behavior. To account for the uncertainty in the process of changing choice, cloud model theory, which is a new cognitive model proposed by Li and colleagues,[14,15] and successfully applied in lots of different research[16,17], was adopted in this paper.

We use the cloud model to predict the driver's charging behavior. When the driver's charging behavior is determined, the average waiting time for each charging station is also determined. An optimization model of charging station location is proposed, which is based on the waiting time. The target of this optimization model is to minimize the time cost to EV drivers.

2. Electric vehicle driver charging behavior prediction

2.1. Cloud model

2.1.1. Introduction of the cloud model. The cloud model was proposed by Deyi Li, a member of the Chinese Academy of Engineering. It is an uncertain transformation model dealing with qualitative concepts and quantitative description.

There are three numerical characteristics in cloud mode,[18] expected value (Ex), entropy (En), and hyper entropy (He). Here Ex is the most representative point of this qualitative concept. This point is the highest point of the cloud. And the degree of membership of Ex is 1. Here En represents a range that can be measured as qualitative concepts. The greater the entropy, the more macroscopic the concept, the wider the range that can be measured. In addition, En reflects the uncertainty of the qualitative concept, also called fuzziness; He is the entropy of entropy, it is used to express uncertainty. It represents the randomness of the sample, namely the discrete degree of cloud droplets. The three numerical methods are as follows:

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

$$En = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n} |x_i - Ex| \tag{2}$$

$$He = \sqrt{S^2 - En^2} \tag{3}$$

$$S^2 = \frac{1}{n-1}\sum_{i=1}^{n} (x_i - Ex) \tag{4}$$

2.1.2. Normal cloud model. The normal cloud model is the most important cloud model. The normal cloud theory is based on universality of the normal distribution and universality of the normal membership function. $\mu =$

$\exp[-\frac{(x_i - Ex)^2}{2En^2}]$ is defined as the normal curve of the normal cloud (X, μ).

The normal cloud is calculated as follows.

1. Generate the normal random number x_i of expectation Ex and standard deviation En.
2. Generate the normal random number En_i of expectation En and standard deviation He.
3. Calculate $\mu_\mathrm{i} = \exp[-\frac{(x_i - Ex)^2}{2En_i^2}]$, where (x_i, μ_i) is the cloud droplets.

2.2. Prediction of EV drivers' charging behavior based on the cloud model

2.2.1. Classification of EV drivers' charging selection behavior. The tolerance of each driver of remaining power is different. Some drivers may choose to charge when the remaining power is 20%, while some drivers may do so at 10%. It is impossible to determine the number of EVs charging at the same time, so the number of the customers at charging stations cannot be determined. In this context, we use a one-dimensional cloud model to classify the charging behavior of EV drivers.

In this stage, the remaining power is the only factor. So a one-dimensional cloud model is used to predict it. First of all, using the distribution graph of the survey data, the three digital characteristics are generated by a backward cloud generator. Then prediction droplets are generated through the forward cloud generator. The cloud generators are shown in Figure 1.

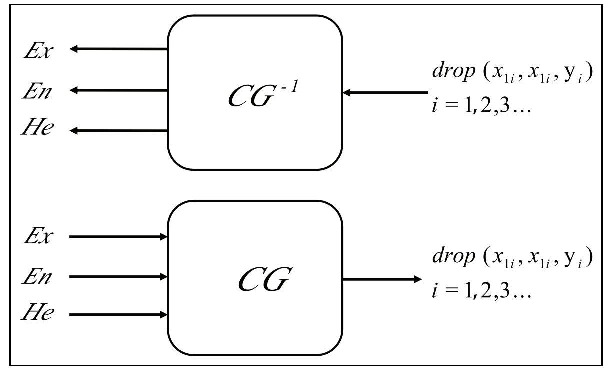

Figure 1. One-dimensional cloud generator.

2.2.2. Prediction of EV drivers' behavior

(1) Planar cloud model.

In real life, people often face a lot of data. But they cannot extract the specific rule knowledge from the data because of the lack of effective processing methods and techniques. We often need such a specific rule as the foundation when we do some related content forecasts. We always need to rely on some prior knowledge to partition the data when extracting an algorithm for data processing. But this division is subjective and cannot reflect the distribution of data. When the data dimension is high, it is more difficult to divide the high-dimensional data space because of the coupling relationship among the dimensions. Therefore, Yang and colleagues[19] presented a planar cloud model. The planar cloud model reflects a complex qualitative concept that comprises two qualitative atomic concepts.

The forward and backward generator of the planar cloud are shown in Figure 2.

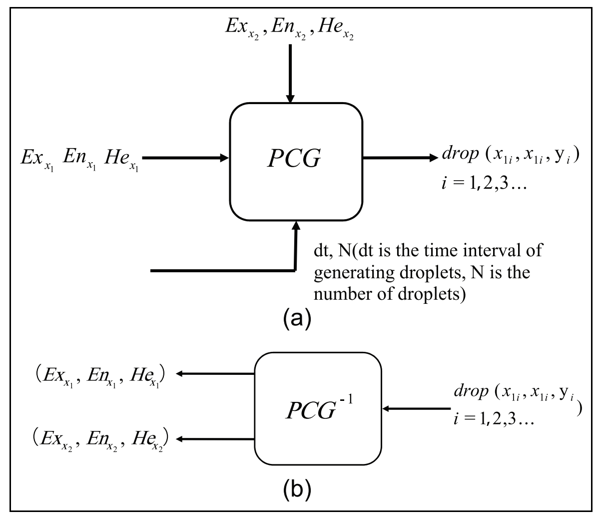

Figure 2. Planar cloud generator: (a) planar backward cloud generator; (b) planar forward cloud generator.

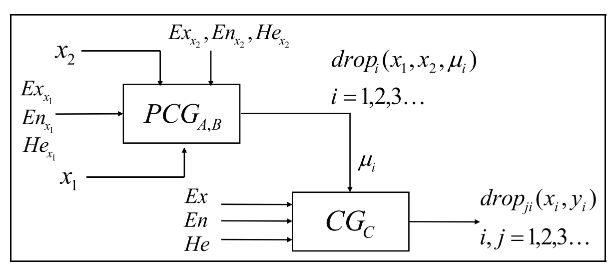

Figure 3. Two-dimensional rule generator.

A two-dimensional X conditional cloud generator and a one-dimensional Y condition cloud generator can create a complex qualitative rule generator. For example, the rule "A and B, then C" cloud generators are shown in Figure 3.

A multi-rule generator is formed when a number of such two-dimensional cloud single-rule generators are combined.

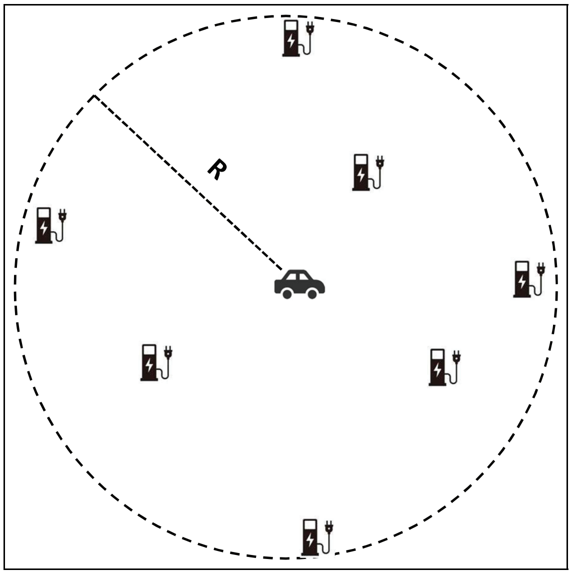

Figure 4. EV drivers' selection of charging stations. Here $R = Q_i^0/s_{ev}$; Q_i^0 = remaining power of electric vehicle i; s_{ev} = consumption power unit distance of each EV.

(2) Prediction of drivers' selection behavior based on the planar cloud model.

We can know whether drivers choose to charge EVs at the moment through the predictions of the cloud model. When the EV driver chooses to charge his vehicle, there are several optional charging stations in the range of the distance that the remaining power can support, as shown in Figure 4. In order to determine the flow of each alternative charging station, we need to predict which charging station EV drivers will choose.

If EV drivers go to the nearest charging station to charge, they may need to wait for charging. It will be a long waiting time even if the EV drivers choose fast-charging mode. If some drivers choose the second nearest charging station to charge, they may not need to wait. Then the total time cost for charging will be less than that for the nearest station. Therefore, in this paper, the waiting time is also considered as an influencing factor when considering the driving distance.

3. Charging station location optimization model

Through the cloud model discussed above, we can predict the number of customers of each charging station. The service capability of each charging station is limited. When the number of EVs is more than the number of charging piles, the drivers need to wait for charging. It will take much of the drivers' time. In this paper, the queuing theory model is used to calculate the waiting time. The optimization model is established, and the model takes the minimum time cost as the objective.

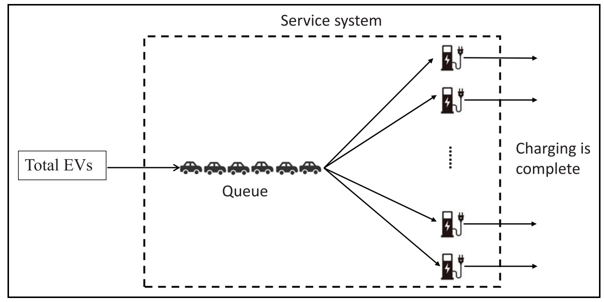

Figure 5. Diagram of EVs queuing system in a charging station.

3.1. Calculation of electric vehicle driver waiting time based on queuing theory

3.1.1. Basic introduction and assumptions. In the queuing system of the charging station location problem, the input process mainly refers to the behavior of EVs arriving at the charging station. The charging behavior of EV drivers has greater flexibility and randomness. This article assumes that the behavior of EVs arriving at the charging station obeys the Poisson distribution with parameter λ. The queuing rules of EVs in charging stations are those of a multi-service window waiting system, and EV drivers obey the first-come first-served rule. Assume that each charging station has C service windows (charging piles), and each charging pile is independent of the others. Assume that the charging time obeys the negative exponential distribution. Parameter μ is the average service rate. Under normal circumstances, it will take 20 min for a charging pile to fill an EV from 20% remaining power in fast-charging mode. Parameterμ is three cars per hour. Queuing mode is as shown in Figure 5.

$$\lambda = \frac{N_{v-j}}{N_1 \times \max\limits_j t_{ij}} \tag{5}$$

Here N_{v-j} = The number of EVs to charging stations j and N_1 = The number of charging piles. Each charging pile's price is 3–5 million. Compared to construction costs, the cost of the charging pile is very small. Thus we assume that the number of charging piles in each charging station is the same.

Here $\max\limits_j t_{ij}$ = the longest traveling time of EV i from the current location to the charging station j.

3.1.2. Queuing model. From the above content we can see that the charging station queuing system mode is M/M/C. The state transition of the system is as shown in Figure 6.

According to the queuing theory[20]:

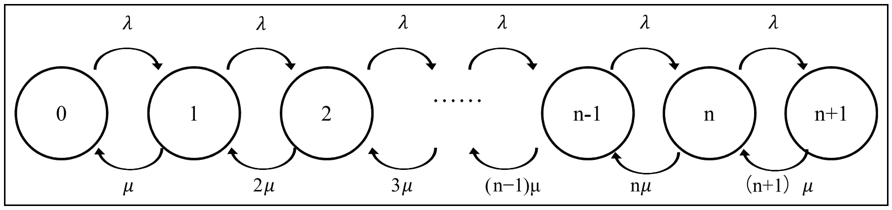

Figure 6. System state transition diagram.

$$P_0 = \left[\sum_{n=0}^{C-1}\frac{1}{n!}\left(\frac{\lambda}{\mu}\right)^n + \frac{1}{C!}\left(\frac{\lambda}{\mu}\right)^C\left(1-\frac{\lambda}{C\mu}\right)^{-1}\right]^{-1} \tag{6}$$

$$\begin{cases} L_p = \left[(C-1)!(C\mu-\lambda)^2\right]^{-1}\lambda\mu\left(\dfrac{\lambda}{\mu}\right)^C P_0 \\ L_s = L_p + \dfrac{\lambda}{\mu} \\ W_p = \dfrac{L_p}{\lambda} \\ W_s = \dfrac{L_s}{\lambda} \\ \mu \geqslant \lambda \end{cases} \tag{7}$$

where L_p is the average queue length, that is the number of waiting EVs in the system;

L_s is the average number of customers, that is the number of EVs in the system;

W_p is the average waiting time;

and W_s is the average sojourn time, that is the dwell time of a EV in a system.

In order to ensure the normal operation of the charging station, the service rate is assumed be greater than the arrival rate.

3.2. The optimization model of charging station location

This paper proposes an optimization model based on queuing theory. The model can ensure that the government can balance investment in the construction of charging stations and can minimize the charging time cost of EVs:

$$\begin{aligned} \min Z = & \sum_{j\in J}\sum_{i\in I} x_{ij}w_j + \sum_{i\in I}\sum_{j\in J} x_{ij}t_{ij} \\ & + \sum_{i\in I}\sum_{i\in J} x_{ij}[Q-(Q_i^0 - e' t_{ij})]/s \end{aligned} \tag{8}$$

$$x_{ij} = \begin{cases} 1, & \text{if EV i choose charging station j to charge} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

Here x_{ij} is determined by the queuing model in Section 3.1.

$$y_j = \begin{cases} 1, & \text{if a charging station is built at alternative station j} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

$$N = \sum_{j\in J} y_j \tag{11}$$

Here t_{ij} = traveling time of EV i from the current location to charging station j;

Q_i^0 = remaining power of EV i;

e' = electricity consumption per unit time of EV;

s = charging speed of charging station;

h_j = construction cost of charging station j;

w_j = average waiting time in charging station j;

Q = total power of an EV;

N = total number of charging stations;

H = total investment cost; and

M = total number of EVs.

Subject to:

$$\sum_{j\in J} x_{ij} \leqslant 1 \tag{12}$$

$$\sum_{j\in J} y_j h_j \leqslant H \tag{13}$$

$$\sum_{i\in I}\sum_{j\in J} x_{ij} \geqslant 90\% M \tag{14}$$

Constraint (12) represents that an EV can be served by not more than one charging station; constraint (13) constrains the total construction cost; constraint (14) expresses the number of serviced EVs, which accounted for more than 90% of all EVs.

4. Model solution

4.1. Predictive solution on electric vehicle driver behavior

4.1.1. The solution on charging behavior classification based on the one-dimensional cloud model. This paper uses questionnaire surveys on the relationship between the remaining power and the probability of selecting charging in the light of classification of charging behavior classification. Three digital characteristics of the one-dimensional cloud mode are generated according to the survey results, and then the required number of cloud droplets are generated through the positive cloud model generator.

Different people have different degrees of tolerance for remaining power. For example, some people think that EVs must be charged when the remaining power is lower than 30%, while others disagree. Therefore, in order to ensure the randomness of the classification and to exclude the contingency, this paper conducts cloud model simulation behavior 10 times to get the average value of the simulation results. On this basis, we use the Bernoulli distribution to randomly generate 0 or 1 to indicate randomness in the decision of whether to charge or not. Here, 1 represents that the EV will be charged, otherwise 0. The greater the probability obtained from the cloud model, the greater the probability that 1 can be randomly generated.

4.1.2. The solution on charging behavior classification based on the two-dimensional cloud model. This paper forecasts the passenger flow of each charging station through the two-dimensional cloud model, considering waiting time and distance. First, we use questionnaire surveys on waiting time and distance, and then divide waiting time into "excellent,""good,""average," and "poor," and divide the distance into "farthest" and "farther""near," and "close." The rules are as follows:

Rule 1: if the waiting time is "excellent" and the distance is "close," the average probability of charging is P_1;
Rule 2: if the waiting time is "good" and the distance is "close," the average probability of charging is P_2;
Rule 3: if the waiting time is "average" and the distance is "close," the average probability of charging is P_3;
Rule 4: if the waiting time is "poor" and the distance is "close," the average probability of charging is P_4;
Rule 5: if the waiting time is "excellent" and the distance is "near," the average probability of charging is P_5;
Rule 6: if the waiting time is "good" and the distance is "near," the average probability of charging is P_6;
Rule 7: if the waiting time is "average" and the distance is "near," the average probability of charging is P_7;
Rule 8: if the waiting time is "excellent" and the distance is "farther," the average probability of charging is P_8;
Rule 9: if the waiting time is "good" and the distance is "farther," the average probability of charging is P_9;
Rule 10: if the waiting time is "excellent" and the distance is "farthest," the average probability of charging is P_{10};
Rule 11: if the waiting time is "good" and the distance is "farthest," the average probability of charging is P_{11}.

The probability that EV drivers choose which station to charge at is forecasted through the two-dimensional multi-rule generator. Using the two-dimensional multi-rule generator and the Bernoulli distribution, we randomly generate 0 or 1 to indicate the randomness of whether to charge at each charging station or not. Among them, 1 represents that the EV will be charged at some charging station, otherwise 0. The greater the probability obtained from the cloud model, the greater the probability that 1 can be randomly generated.

Everyone has a different perception on waiting time and distance. For example, some people think that a wait of 20 min is too long and they cannot accept it; some people may not think so. This paper predicts driver behavior 10 times to obtain the average value of the simulation results. Moreover, it can ensure the accuracy of the prediction results and the randomness of samples, and exclude contingency.

4.2. SCE-UA algorithm for electric vehicle charging station location

The optimization model of EV charging station location is a nonlinear integer programming problem; it cannot be solved with the traditional analysis method. This paper uses the SCE-UA algorithm to solve the optimization model.

The SCE-UA algorithm is also known as a hybrid evolutionary algorithm. Similar to other heuristic algorithms, the SCE-UA algorithm has also been researched and applied by a number of scholars.[21–23] It is a global optimization algorithm, and it combines the characteristics of complex method, random search, and biological competitive evolution.

The SCE-UA algorithm has strong capabilities for global optimization. In the probabilistic optimization of hydrological model parameter subspace, Kucezara[24] compared the search performances of the SCE-UA algorithm, genetic algorithm, and MSX algorithm (using simplex method and quasi-Newton method respectively). The results showed that the SCE-UA algorithm had better robustness and better convergence. Although the genetic algorithm had a fast convergence rate in the initial stage of evolution, it could not find the effective optimal solution in the region near the optimal solution.

The essence of the SCE-UA algorithm is to regard the global search process as a natural evolutionary process. The sample points first form a group. Then the group is divided into several subgroups, which are complexes. Each complex evolves independently, searches in different directions, and gradually evolves into a certain stage in its best search direction. After several generations of evolution, the groups are mixed. A new group is generated through the mixing process and the evolution process is restarted. This process enhances the survival ability of the population and gradually converges the solution to the global optimum by sharing the information obtained from each independent group.

Specific steps of minimization problems of the algorithm solution SCE-UA are as follows[21]:

Step 1: Parameters setting. Initialize the number of complexes p ($p \geqslant 1$) and the number of points m in each complex. Compute the sample size as $s = pm$.
Step 2: Generate a random sample of s points $X[x_1, x_2, x_3, \cdots, x_m]$ in feasible solution space; compute the function value f_i of the optimization model at each point x_i.
Step 3: Rank the s function values $f_i(i = 1, 2, \ldots, s)$ of the optimization model in ascending order and store them in array $D = \{(x_i, f_i), i = 1, 2, \ldots\ldots, s\}$ such that $i = 1$ represents the smallest function value.
Step 4: Partition D points into p complexes $A^1, A^2, \ldots, A^p$, each containing m points.
Step 5: Generation of offspring. Evolve each complex $A^k, k = 1, 2, \ldots, p$ using the competitive complex evolution algorithm.
Step 6: Evolve each complex and shuffle them into points, then generate new complexes; repeat step 5.
Step 7: Check for convergence. If convergence criteria are satisfied, stop; otherwise return to Step 3.

5. Numerical tests

In this paper, two examples are given to verify the feasibility of the model and algorithm. We first verify the feasibility through a small network, then we optimize the EV charging station location in Dalian.

5.1. Simple case

As shown in Figure 7, it is a small network consisting of 50 EVs and 10 alternative charging stations. Optimize the charging station location on this basis. We must ensure that 90% of all EVs are served. The objective, minimum total time cost including waiting time, should be obtained under the constraint of total construction cost. The results are as follows.

Table 1 shows the optimal charging station location plan when establishing 4–8 charging stations. As shown in Table 1, the greater the number of charging stations established, the smaller the average waiting time, and the smaller the total time cost. Due to the total construction cost constraint, the time cost is minimized when eight charging stations are established. The minimum time cost is 1173.1 min. So, in this small case, the optimal charging station location scheme is to establish eight charging stations, namely number 2, 3, 4, 5, 6, 7, 9, 10 alternative charging stations.

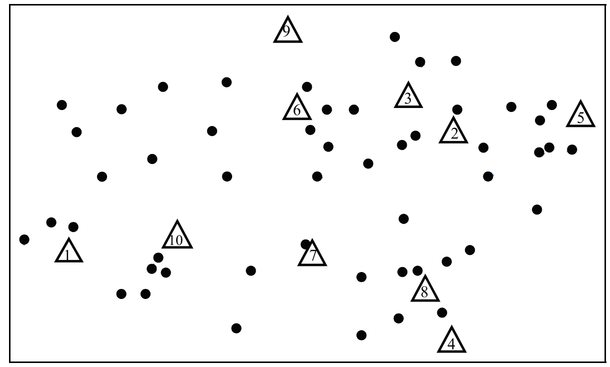

Figure 7. Charging network for the small case.

5.2. Case of Dalian

Dalian is an important coastal city in east China, located in the south of Liaodong peninsula. It covers an area of 13,237 km^2 and has a population of 6.69 million. Dalian is in the first batch of cities in China to popularize new EV cars. The generous subsidies for new EVs is up to 147,500 yuan, which is about 50% of the price of a common electric car. New electric cars have the favor of many people due to there being no-purchase-tax policies for them. More than 2000 new-energy vehicles have been put in the fields of bus, postal, sanitation, units and the private purchase in Dalian. The vehicles include pure electric passenger cars, plug-in hybrid buses, plug-in hybrid electric passenger cars, and others. There is great demand for EV charging in Dalian. Therefore, it is necessary to optimize the charging stations location in the city.

Table 1. Result of small case.

Scenario	Number of EVs	Number of CSs	Project	Time cost (min)	Average waiting time (min)	Cost (million $)
1	50	4	3,4,5,10	1867.3	6.72	1900.26
2	50	5	3,4,5,6,10	1719.5	4.12	2325.64
3	50	6	3,4,5,6,9,10	1500.3	4.66	2821.72
4	50	7	2,3,4,5,6,9,10	1386.6	4.96	3262.87
5	50	8	2,3,4,5,6,7,9,10	1093.1	2.14	3704.98

CS, charging station; EV, electric vehicle.

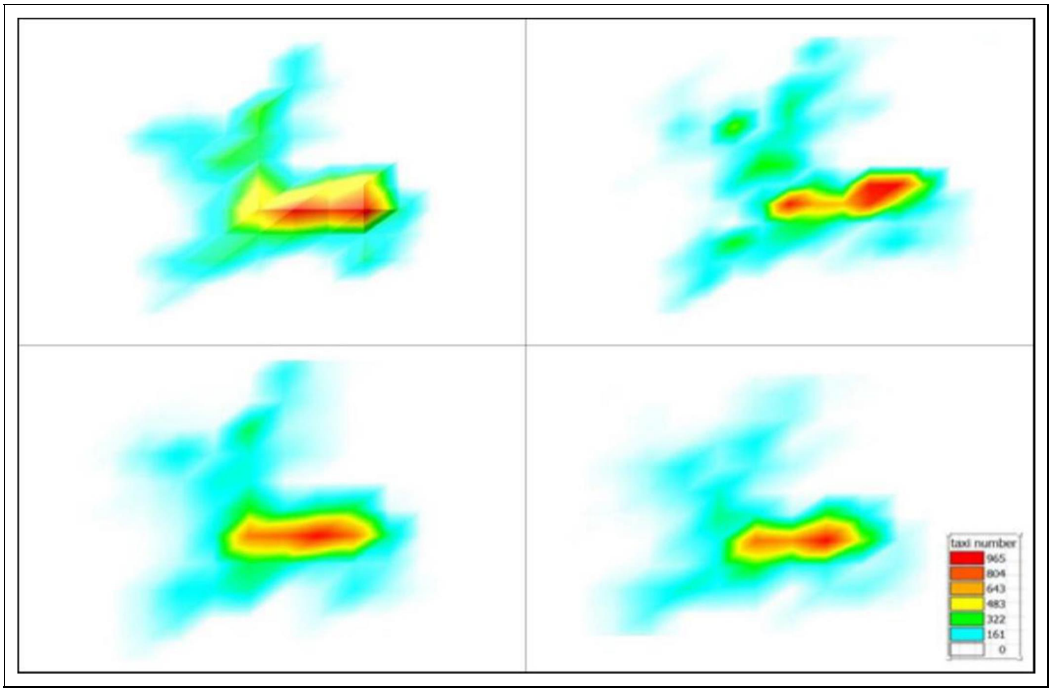

Figure 8. Distribution of charging demand in the study area on different days.

5.2.1. Data collection and parameter calibration. In this paper, gas stations existing in Dalian are selected as alternative sites for charging stations. While the location of EVs is changing, within a certain period of time it reached, to a certain extent, a dynamic balance (as visualized in Figure 8). The distribution of EVs and alternate charging stations in Dalian are shown in Figure 9.

Other parameters are shown in Table 2.

5.2.2. Results presentation. In the forecast of driver behavior, we first carried out the questionnaire survey and made predictions accordingly. The results of the survey about the charging choice behavior of the EV drivers are shown in Figure 10. From the questionnaire, the cloud model of charging choice behavior classification of EV drivers is a decline cloud model. The expected value is 23%. Programmed with MATLAB, we used the cloud model to predict the behavior of EV drivers. Predicted results are shown in Figure 11. When the remaining power is less than 23% of total electricity, the probability of the driver choosing to charge is very high; when the remaining power is more than 23% of total electricity, the probability will decrease with the increase of remaining power. In Figure 11, the charge selection probability of the EV driver obtained by the cloud model is approximately the same as that of the survey data in Figure 10. The choice probability in Figure 11 also preserves the randomness of driver selection behavior.

Table 2. Value of parameters.

Parameters	Values
Number of candidate charging stations	58
Standard speed of electric vehicle	50k mph
Electricity consumption speed of electric vehicle	8.5 kW
The initial electricity of electric vehicles	200 kWh
Electricity consumption speed of battery distribution vehicle	40 kW

Similarly, by the questionnaire survey and planar cloud model, we get the EV drivers' charging behavior in alternative stations. Then, through the SCE-UA algorithm, EV charging station location is optimized. We assume that each charging station has 10 charging piles.

In the fixed cost constraints, we assume that the number of EVs is 1000. We optimize charging station location without the driver behavior prediction mode and with the driver behavior prediction mode respectively. The optimization results are shown in Table 3. If we do not predict driver behavior, which assumes that the driver chooses the nearest charging station when they need to charge, the total time cost is 27.28% more than the total time cost in driver behavior prediction mode, and the average waiting time is 1.68 min more. Therefore, before optimizing the charging station location, it is necessary to forecast the charging behavior of the drivers.

When the total number of EVs that need to be served is different, the optimization result will be different. So we

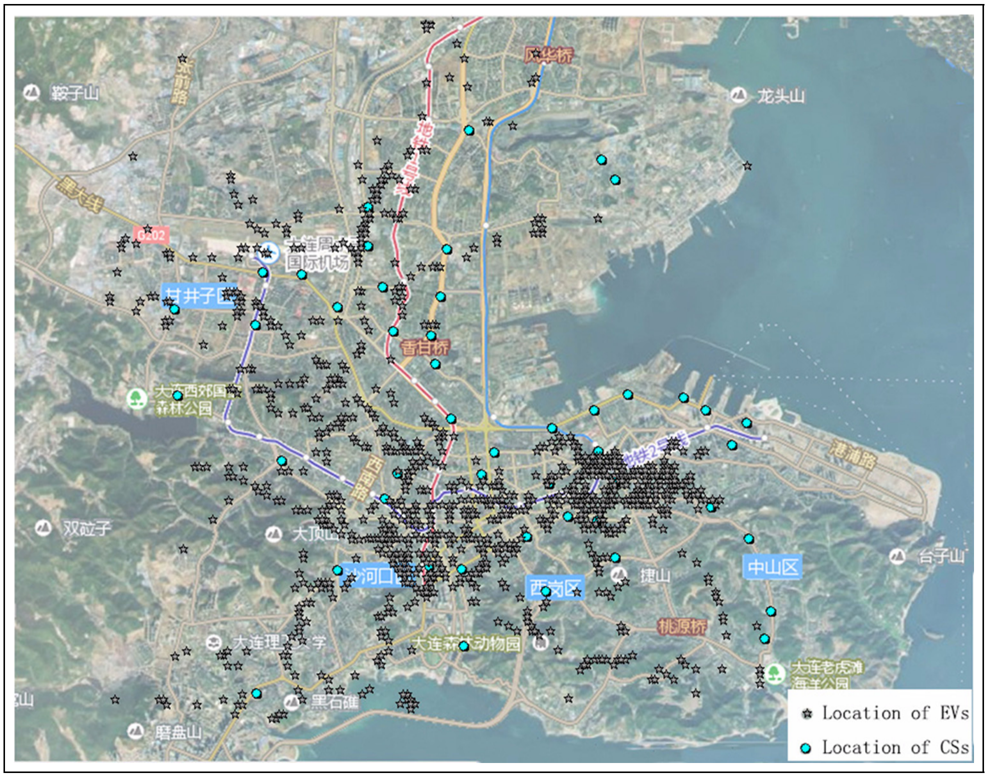

Figure 9. The distribution of EVs and alternate charging stations in Dalian.

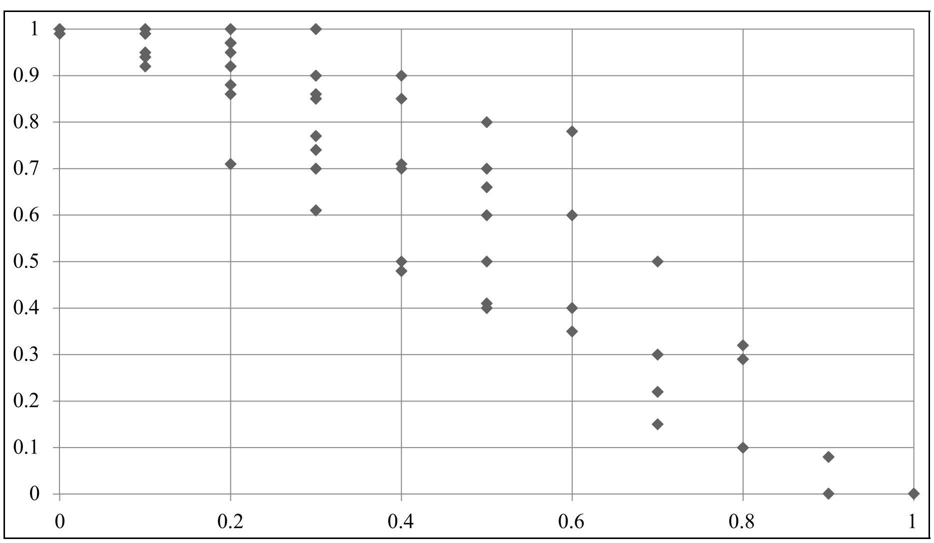

Figure 10. Survey data.

Table 3. Optimized result with or without behavior prediction of EV drivers.

Scenario	Behavior prediction	Number of charging stations	Project	Time cost (min)	Average waiting time (min)	Cost (million $)
1	N	13	1,3,6,15,17,19,22,25,27,33,42,44,56	1.9365e + 005	4.43	56.3754
2	Y	13	1,3,15,17,19,22,25,27,33,36,42,51	1.5214e + 005	2.75	55.2123

Table 4. Optimized result of different number of EVs.

Scenario	Number of electric vehicles	Number of charging stations	Project	Time cost (min)	Cost (million $)
1	500	10	1,3,15,17,22,25,27,33,42,51	0.9432e + 005	41.6077
2	1000	13	1,3,15,17,19,22,25,27,33,36, 42,51	1.5214e + 005	55.2123
3	1500	15	1,3,7,15,17,19,22,25,27,33,36,42,51,52,56	2.5823e + 005	67.1341
4	2000	18	1,3,7,13,15,17,19,22,25,27,33,36,37,42,46,51,52,56	3.7214e + 005	75.8935
5	2500	19	1,3,7,13,15,17,19,22,25,27,33,36,37,42,46,51,52,54,56	5.2156e + 005	8673.69

Table 5. Optimized result of different cost constraints.

Scenario	Cost constraint	Number of charging stations	Project	Time cost (min)	Average waiting time (min)	Cost (million $)
1	50	11	1,3,15,17,22,25,33,42,46,51	1.9175e + 005	3.58	47.8463
2	60	13	1,3,15,17,19,22,25,27,33,36,42,51	1.5214e + 005	2.75	55.2123
3	70	15	1,3,7,13,15,17,22,25,27,33,36,42,43,56	1.3523e + 005	2.06	68.5738

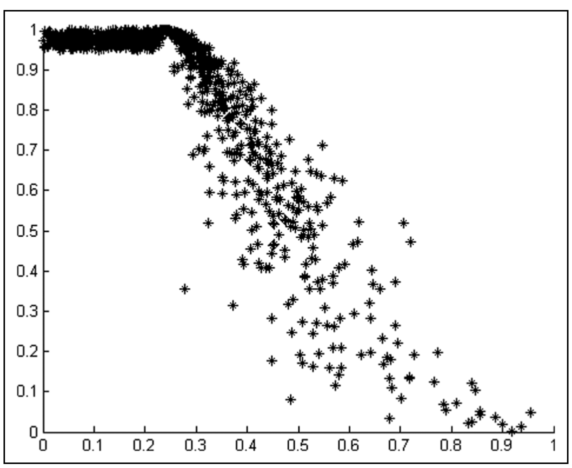

Figure 11. Cloud model.

optimize charging station location against the background of different numbers of EVs. The optimization results are shown in Table 4.

As shown in Table 4, when more EVs need to be charged, more charging station need to be constructed, and the construction costs increase.

In this paper, when construct the optimization model, we assume that construction costs cannot be more than the total cost constraints. When the government invests in EV charging stations, it needs to ensure that the cost of investment is reasonable. Therefore, the cost of investment should also be a factor when optimizing the charging station site. Table 5 shows the optimal scheme under different investment cost constraints, when the number of EVs is 1000.

As can be seen from Table 5, with the increase in the cost constraint value, the number of charging stations will increase, while the average waiting time and the total time cost will decrease. When the cost constraint of investment is $60 million, the number of charging stations is 13, the time cost is 1.5214e + 005 min, and the average wait time is 2.75 min. Compared to the case when the cost constraint is $50 million, although the cost of investment increased by 15.39%, the total time cost is reduced by about $20.7%, and the average waiting time is reduced by 0.83 min. Compared to the case when the cost constraint is $50 million, although the total time cost increased by 12.50%, and the average waiting time increased by 0.69 min, the cost of investment increased by 15.39%. Therefore, through the comprehensive comparative analysis, it is more reasonable when the upper limit of the investment cost is set at $60 million.

6. Conclusions

The EV is seen as an effective way to alleviate the current energy crisis and environmental problems. However, the lack of supporting charging facilities is still a bottleneck in the development of EVs in the Chinese market. In this paper, the cloud model is used to predict drivers' charging behavior. An optimization model of charging stations is proposed, which is based on the waiting time. The SCE-UA algorithm is used to solve the optimization model. The method is applied to Dalian China to optimize the charging station location. Through an example, we prove the necessity of EV driver behavior prediction and the feasibility of the charging station location optimization method proposed in this paper. In the case of optimization with or without behavior prediction of EV drivers, the total time costs without behavior prediction of EV drivers is 27.28% more than the total time cost in driver behavior prediction mode, and the average waiting time is 1.68 min more. Therefore, before optimizing charging station location, it is necessary to forecast the charging behavior of drivers. We also analyzed the constraints on investment cost. It is believed that the methodology followed here can provide government with good insight into charging facilities and the development of EVs.

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