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Research Article

Electric Vehicle Charging Infrastructure Location Optimization with Mixed and Forecasted Charging Requirements

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Electric vehicles are not widely adopted without proper charging infrastructure, despite their environmental benefits and growing popularity in transportation. This paper focuses on the location problem of charging infrastructure to achieve a more optimized charging facility layout. The charging demands of electric vehicles can be divided into two categories. The first category is generated at network points such as shopping malls, office buildings, parking lots, and residential areas. The second category is generated along the flow of network paths, such as on the highway and on the way to and from work. The goal of this problem is to maximize both categories of charging demands using a nonlinear integer programming model. We introduce the spatial intersection model to obtain the data on path demand. The spatial intersection model is introduced to obtain data on path demand. In addition, future demand is taken into account in the optimization through data forecasting. Then, the greedy algorithm is designed to solve the optimization model. The effectiveness is proved by a lot of random experiments. Finally, the effects of parameters are analyzed by a case study. The location decision of charging stations for both demands is more reasonable than only one type of demand consideration. The proposed model ensures the coverage and appropriate extension of the charging network.

1. Introduction

In recent years, due to the energy crisis and serious environmental pollution, the Chinese government has vigorously promoted the development of new energy vehicles. National and local governments have adopted a series of incentive policies for the promotion of . With the support of these policies, the market size of EVs in China has increased rapidly, as shown in Figure 1. However, current EV penetration is far behind government planning. The new Energy Vehicle Industry Development Plan (2021–2035) puts forward the new goal that by 2025, the proportion of EV sales should reach about 20% of the total vehicle sales [1], but now the proportion is 5.4%. Among these reasons for the slow promotion, one of the major problems is the backward charging of infrastructure construction. On the one hand, the number of existing charging stations seriously lags behind the EV development plan. On the other hand, the of charging stations is unreasonable. In 2018, the utilization rate of public charging stations was less than 10%, which is difficult for operating enterprises to make a profit [2]. For example, Wuhan has more EV charging piles than the number of EVs, but the EV is still difficult to charge; the daily utilization rate of public charging piles in Beijing is only 6% to 7%, and they are idle most of the time; TELD, the new energy company, has suffered losses for four consecutive years, with a cumulative loss of 600 million yuan.

The purpose of this paper is to reasonably locate the charging stations to maximize the number of charging demands. The previous literature on the location of charging stations can be mainly divided into two categories [3]. One category assumes the charging demands generated in network points, such as in shopping malls, office buildings, parking lots, and residential areas. This kind of research is usually based on the coverage location model, which sets the coverage radius of the charging station and aims to maximize the charging demands within the coverage radius [4–8]. The other research studies the charging demands as flows generated on the network paths, such as on the highway and on the way to and from work. This kind of research is often based on the flow interception location problem (FILP) [9–14].

However, in reality, the charging demands are not so clear to distinguish. One charging station intends to provide service to both demands. For example, the charging station on the main road serves lots of the charging demands on this path and its surrounding paths but also provides services for nearby communities, shopping malls, and office buildings around it. Similarly, charging piles built in office buildings and shopping malls can also charge EVs passing by. Therefore, this paper considers the charging demands from points and paths at the same time, through the weight factor, adjusting the influence of two types of demands on the location decision.

But actually, it is difficult to obtain the flow between origin-destination (O-D) pairs, which is assumed to be given in traditional FILP. However, in general, only transport with the given route can obtain the flow of O-D pairs, such as trains [15] and buses [16]. Moreover, in a large-scale complex network, it is almost impossible to obtain each O-D pair of traffic flow, even if the traffic on each network edge can be obtained through advanced technologies, such as monitoring and data crawling. In this paper, we introduce the spatial intersection model (SIM) to estimate the charging demands of each O-D pair. SIM is first applied to estimate the demand of the retail industry; the number of retail customers attracted from a town around the retail location is directly proportional to the population size of the town and inversely proportional to the distance between the two places [17]. Then, it is applied to measure the trade flows between two countries and traffic flows between two places [18].

In the existing empirical research or case analysis on the location of charging stations, the charging demand concerns the number of existing EVs [5–8, 11–14, 18, 19], assuming that charging demand is highly stochastic, with a scenario-based model to describe it; however, all scenarios are described on the current observation. Even scholars who study the expansion of multiperiod charging stations assume that the number of EVs will remain unchanged over each period [10, 16], which is seriously inconsistent with the current development of EVs. From Figure 1, the market size of EVs is increasing rapidly, so the design of charging stations must consider the operation in the future, or the charging station will be "outdated" after its establishment.

Compared with traditional vehicles, the most significant feature of is trip range restriction. Due to the limitations of battery technology, endurance cannot be compared with traditional vehicles, which causes range anxiety for drivers. Therefore, the distance between adjacent charging stations should not be too far. According to the data released by the National Energy Administration, the distance between adjacent public charging stations in China is no more than 50 km [20], which is adopted as one constraint in our model.

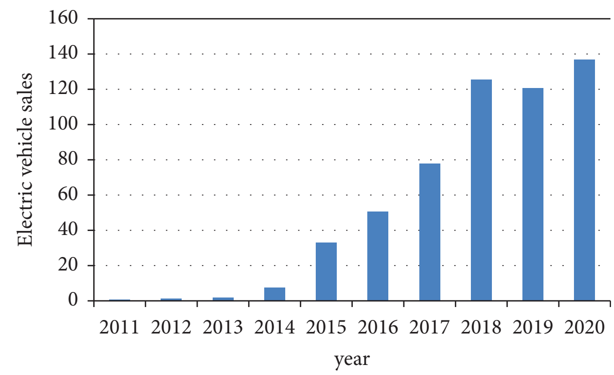

Figure 1: Annual sales volume of EVs in China from 2011 to 2020 (unit: 10,000).

Our model is an NP-hard problem, so an effective algorithm is necessary [21–24], and we design greedy heuristics to solve it.

For this paper, the main contributions are as follows:

(1) In reality, charging demands are generated from the points and paths, and the charging station intends to provide service to both demands. Therefore, we consider mixed charging demands in our location model.

(2) As EVs are increasing rapidly, we consider the future number of EVs as the basis for the design of charging stations. This paper proposed a prediction method for EV numbers with neural networks based on a government plan.

(3) As our model is an NP-hard problem, a heuristic algorithm for large-scale examples is proposed.

2. Model Establishment

2.1. Parameters and Decision Variables. First, the symbols are defined as follows:

Sets:

V: set of all points on the network
I: set of candidate locations of charging stations
P: set of all paths
H: set of all combinations of charging stations

Parameters:

θ: coefficient, $\theta \in [0, 1]$
w_j: the number of charging requirements at point j
f_ρ: the number of charging requirements on path ρ
m: the number of total charging stations to be built

Decision variables:

a_{ij}: if point j is within the coverage radius of charging station i, then $a_{ij} = 1$; otherwise, $a_{ij} = 0$, $i \in I$, $j \in V$
$b_{\rho h}$: if the charging station combination h can support an EV to complete the round trip of path ρ, $b_{\rho h} = 1$; otherwise, $b_{\rho h} = 0$, $h \in H$, $\rho \in P$
v_h: if all points in combination h establish charging stations, then $v_h = 1$; otherwise, $v_h = 0$, $h \in H$

v_{hi}: if charging station i is in combination h, then $v_{hi} = 1$; otherwise, $v_{hi} = 0$, $h \in H$, $i \in I$

z_j: if charging demands at point j can be served, then $z_j = 1$; otherwise, $z_j = 0$, $j \in V$

x_i: if a charging station is established at point i, then $x_i = 1$; otherwise, $x_i = 0$, $i \in I$

y_ρ: if EVs on path ρ can complete the round trip, then $y_\rho = 1$; otherwise, $y_\rho = 0$, $\rho \in P$

2.2. Mathematical Model. Through the above symbol definition, the charging station location model is established as follows:

$$\max Z = \theta \sum_{j \in V} w_j z_j + (1-\theta) \sum_{\rho \in P} f_\rho y_\rho, \tag{1}$$

subject to

$$\sum_{i \in I} x_i = m, \tag{2}$$

$$\sum_{h \in H} b_{\rho h} v_h \geq y_\rho \quad \forall \rho \in P, \tag{3}$$

$$v_{hi} x_i \geq v_h \quad \forall h \in H; i | v_{hi} = 1, \tag{4}$$

$$\sum_{i \in I} a_{ij} x_i \geq z_j \quad \forall j \in V, \tag{5}$$

$$x_i, y_\rho, z_j, v_h \in \{0,1\} \quad \forall i \in I,\ j \in V,\ \rho \in P,\ h \in H. \tag{6}$$

Objective function (1) represents maximizing of charging requirements from the covered points and paths by charging stations. Constraint (2) indicates that the number of charging stations to be established is m. Constraints (3) means that at least one combination that can support the EV to complete the round trip can be found, and all charging stations in the combination have been established, then the charging requirements on the path are covered. Constraints (4) mean v_h holds to zero unless all the charging stations in combination h are established. Constraints (5) indicate that charging requirements at a point j can be served only when the point j is within the coverage radius of the point i where the charging station has been established. Constraints (6) describe the binary restrictions.

2.3. The Relationship between f_ρ and w. Let $G(V, E)$ be a network where V is the set of demand points, E is the set of arcs, and I is the set of candidate locations of charging stations ($I \subseteq V$). It is assumed that the driver knows the shortest path ρ between O-D and selects it as the driving path. f_ρ represents the charging requirements on the path ρ. Berman et al. [9] and Hodgson [25] proposed. Assumes that the flow on the path between each O-D pair is known, and once a facility is built at a point, all flows passing through that point are covered.

However, in reality, the network is complex, and the acquisition of the flow of each O-D pair is difficult. The common method to obtain the data on O-D pairs and charging requirements is tracking the driving trajectory of electric taxis through GPS [26], but it is very difficult for the trajectory of other general EVs. Other methods are through technologies such as monitoring or data crawling to obtain the edge flow of the network [27], but it is not enough because monitoring cannot discriminate which flow belongs to which O-D pair. Still, the flows between O-D pairs cannot be made available. In this paper, SIM is introduced to obtain f_ρ from w by using the following formula [17]:

$$f_\rho = k \frac{\left(w_i w_j\right)^\alpha}{d_{ij}^\beta}. \tag{7}$$

From (7), the flow between the two points is directly proportional to the point demands but inversely proportional to the distance between the two points. In our model, ρ is assumed to be the path with the shortest distance between points i and j. There are a total of $C_{|V|}^2$ paths, in which $|V|$ represents the number of point generation charging demands. w_i and $w_j\,(i, j \in V)$ represent the charging demands generated at points i and j, and d_{ij} shows the shortest distance between points i and j. β indicates the sensitivity of distance to spatial interaction. The larger the value of β, the weaker the interaction between points i and j. The coefficients k, α, and β can be derived from the regression models based on historical data.

2.4. Determination of w Parameters. Due to the rapid development of EVs, the construction of charging stations must take into account the future number of EVs to be served. Therefore, the input parameter w in the model should be the future predicted value rather than the current value of the point charging requirement. In this paper, a nonlinear neural network tool is adopted for time series prediction [28–30] which is based on historical data. But, due to the short development time of EVs, there is less historical data collection. Furthermore, its development is mainly driven by government policies; therefore, prediction is unreasonable directly according to historical data like the previous research [31]. This paper proposes a prediction framework. This framework first predicts the number of vehicles in the future by the nonlinear neural network. Due to the long history of automobile development and the rich historical data of vehicles, the prediction of the number of vehicles is much more accurate than the direct prediction of the number of EVs. Then, combined with government planning, we can get the predicted number of EVs.

The model adopts a nonlinear autoregression with exogenous inputs (NAR) neural network, which can be described by the following formula:

$$y(t) = f\left(y(t-1), y(t-2), \ldots, y(t-p)\right), \tag{8}$$

where f is a nonlinear function, and the value of y at t time depends on the previous p values of y.

Assuming that the occupation ratio of the local EV is the same as the national average, the prediction framework is as follows:

Step 1: according to the historical data of national vehicle ownership, the NAR neural network is used to predict the future national vehicle ownership, VQ. According to the future national EV ownership EVQ planned by the government, the occupation ratio of national EVs in the future is obtained as $\theta = EVQ/VQ$.

Step 2: according to the historical data of vehicle ownership in a local area, the NAR neural network is used to predict the future local vehicle ownership VQ'. The future EV ownership in this region is $EVQ' = VQ'\theta$.

Step 3: allocate the number of EVs at each demand point according to the population proportion $w_i = EVQ' pi\%$, where $pi\%$ is the population ratio of point i.

2.5. Mileage Limit. Nowadays, the battery capacity of EVs is not enough to ignore the distance between adjacent charging stations, that is, the trip mileage limit. EV users are always afraid that the battery is out of power before they find the next charging station, which is called trip mileage anxiety. In order to reduce or even eliminate trip mileage anxiety, we set a reasonable trip mileage limit between adjacent charging stations before construction. If the distance between adjacent charging stations is more than the trip mileage limit, drivers will produce strong mileage anxiety. As mentioned above, the distance between charging stations established in China is no more than 50 km [20], so we set the trip mileage limit to 50 km.

In the mathematical model, we adopt the method in [32] to express the trip mileage limit. It is assumed that (1) when the distance between two adjacent charging stations exceeds the trip mileage limit, the charging stations cannot cover the path; (2) the covered path is a round-trip path; (3) the charging station can only be established at the point; (4) if there is no charging station at the starting point, the initial driving mileage of the EV is half of the trip mileage limit. Constraints (3) and (4) mean that at least one combination h that can support the EV to complete the round trip can be found, and all facilities in the combination h have been established, then the EV can complete the round trip. These constraints are obviously different from FILP in which as long as there is a facility on the O-D path, the flow can be intercepted.

3. Algorithm

As the charging station location model is an NP-hard problem, with the expansion of the model scale, the computing time of the accurate algorithm will be very long. It is necessary to find an effective algorithm for this kind of problem. In this paper, a greedy algorithm is used to solve the problem, and the solving steps are described as Algorithm 1.

4. Simulation Experiments

In this section, random examples are generated to verify the effectiveness of the greedy algorithm by comparing it with the exact solutions. The exact solutions are obtained by using the enumeration algorithm. A connected network is randomly generated, the point demand is randomly generated in the interval (0, 10), the distance between two adjacent points is distributed in the interval (0, 20), and the connection probability between points is 0.5. Because the calculation time of the enumeration algorithm is long, the number of points and charging stations cannot be large. In this paper, the number of network points is set to be 20, 25, 30, 50, 100, and 150, and the number of charging stations is set to be 3, 4, 5, 10, 15, and 20. When the point number of networks is 50 and the number of charging stations is 5, the computational time of enumeration exceeds 2 hours. We set the upper bound of the enumeration algorithm time to 2 hours. Different network points and charging stations constitute a group of examples, and 10 examples are generated randomly in each group. A total of 170 examples are generated in this section to verify the effectiveness of the greedy algorithm. The parameters of SIM are set as follows [25]: $k = 0.5$, $\alpha = 0.5$, and $\beta = 2$. Other parameters: $\theta = 0.5$, the point coverage is 8, and the trip mileage limit is 10. The calculation results of the greedy algorithm are shown in Table 1.

From Table 1, it can be found that the gap of the greedy algorithm is small, no more than 5.48%. Usually, the optimal solution can be found by using the greedy algorithm, and the lowest group is 70%. With the increasing number of points and charging stations, as computational time limitations of enumeration, the greedy algorithm shows more advantages in computational time and result accuracy than enumeration.

However, it is found that the trip mileage limit has a great impact on the accuracy of the greedy algorithm, as shown in Table 2. The trip mileage limit is set to be 0.5, 1, 1.5, 2, and 5, respectively, and 10 examples are randomly generated for each value of the trip mileage limit with 25 points and 5 charging stations. It is found that the smaller the trip mileage limit, the greater the gap. The performance of the greedy algorithm in our model is similar to that in the literature [32]. When the trip mileage limit is 0.5, the maximum gap reaches 75.25%, and only 4 of the 10 examples reach the optimal solution. When the trip mileage limit is too small, the greedy algorithm is difficult to find the optimal combination of charging stations to cover the round trip of a path because the greedy algorithm only adds one charging station each time.

Input: V, I, m, $w_j\,(j \in V)$, α, β, k, θ, coverage radius and trip mileage limit
Output: X
adopt dijkstra algorithm to calculate the shortest distance d_{ij} between any two points $i\,(i \in I)$ and $j\,(j \in V)$ and the shortest path set P
adopt SIM (fomular (7)) to obtain path demands f_ρ of all paths in P
for $i \in I$
for $j \in V$
if d_{ij} is no more than the coverage radius
$a_{ij} = 1$
else
$a_{ij} = 0$
endif
endfor
endfor
initialize $X = \Phi$
for $n = 1{:}\ m$
for $j \in V \backslash X$
$W(j) = 0$
endfor
for $j \in V \backslash X$
for $i \in I$
$W(j) = W(j) + a_{ij} w_i$
endfor
endfor
for $j \in V \backslash X$
$F(j) = \sum_{\rho \in P(X \cup \{j\})} f_\rho$, $P(X)$ is the set of paths that is covered by charging station set X
endfor
for $j \in V \backslash X$
$Z(j) = \theta W(j) + (1 - \theta) F(j)$
endfor
$j^* \leftarrow \operatorname{argmax}_{j \in V \backslash X} \{Z(j)\}$
$X = X \cup \{j^*\}$
$V = V \backslash \{j^*\}$
for $i \in I$
if $a_{ij^*} = 1$
$w_i = 0$
endif
endfor
for $\rho \in P(X)$
$f_\rho = 0$
endfor
endfor

Algorithm 1: The greedy algorithm for the charging station location model.

5. Case Analysis

Cixi City is located on the Bank of Hangzhou Bay, Zhejiang Province, with a population of 1,051,000. It is composed of 4 streets and 15 towns, as shown in Figure 2. In Figure 2, different sizes of points indicate different sizes of population. This case takes the predicted number of Cixi EV in 2030 as the demand parameter.

We adopt the GUI interface in MATLAB and Bayesian regularization back-propagation as the training functions. Through repeated experiments, a nonlinear autoregressive network with 1 : 5 feedback delay is created, the number of hidden layer neurons is 10, and the response of a delayed neural network is eliminated. According to the historical data of national vehicle ownership from 1940 to 2020, it is predicted that national car ownership will be 335.6 million in 2030. According to the historical data on vehicle ownership in Cixi from 1993 to 2020, it is predicted that the vehicle ownership in Cixi will be 0.57 million in 2030. Figure 3 shows the error between the national vehicle ownership forecast data and the actual data. The absolute error value is no more than 500. It can be seen that the error is very small, and the forecast data is reliable. Figure 4 shows the forecast trend of national car ownership. Figure 5 shows the error between the predicted car ownership data and the actual data in Cixi City. The relative error does not exceed 13%, and the predicted data are reliable. Figure 6 shows the forecast trend of vehicle ownership in Cixi City. According to the development of energy-saving and new energy vehicles plan, by 2030, the number of EVs in China will reach 80 million, and the percentage of EVs in the total number of vehicles will be 23.8%. Assuming that the percentage of EV ownership in

Table 1: Performance of the greedy algorithm.

Point number	m	Minimum gap (%)	Maximum gap (%)	Average gap (%)	Percentage of optimal solution (%)	Average computational time of the greedy algorithm (unit: s)	Average computational time of enumeration (unit: s)
20	3	0	5.84	0.72	70	2.08	27.16
	4	0	0.41	0.04	90	2.64	151.97
	5	0	0	0	100	2.89	413.25
25	3	0	0	0	100	4.05	119.05
	4	0	0	0	100	3.88	502.38
	5	0	0030	0	100	5.33	2003.40
30	3	0	0	0	100	6.95	221.58
	4	0	0	0	100	6.72	1492.20
	5	0	0.06	0.006	90	7.25	7585.80
50	5	−11.08	−0.09	−5.58	100	10.74	7200.00
	10	−21.89	−2.62	−10.34	100	31.10	7200.00
100	5	−11.17	−0.92	−16.06	100	113.19	7200.00
	10	−42.04	−4.33	−27.87	100	245.07	7200.00
150	10	−111.22	−1.56	−40.87	100	546.83	7200.00
	20	−9.79	−1.68	−4.76	100	2043.53	7200.00
200	10	−81.50	−1.00	−41.25	100	1698.80	7200.00
	20	−15.64	−4.23	−29.00	100	4377.60	7200.00

Table 2: Influence of the mileage limit on the accuracy of the greedy algorithm.

Mileage limit	Minimum gap (%)	Maximum gap (%)	Average gap (%)	Percentage of optimal solution (%)
0.5	0	75.25	13.35	40
1	0	22.78	3.07	70
1.5	0	3.47	0.35	90
2	0	1.08	0.13	80
5	0	0	0	100

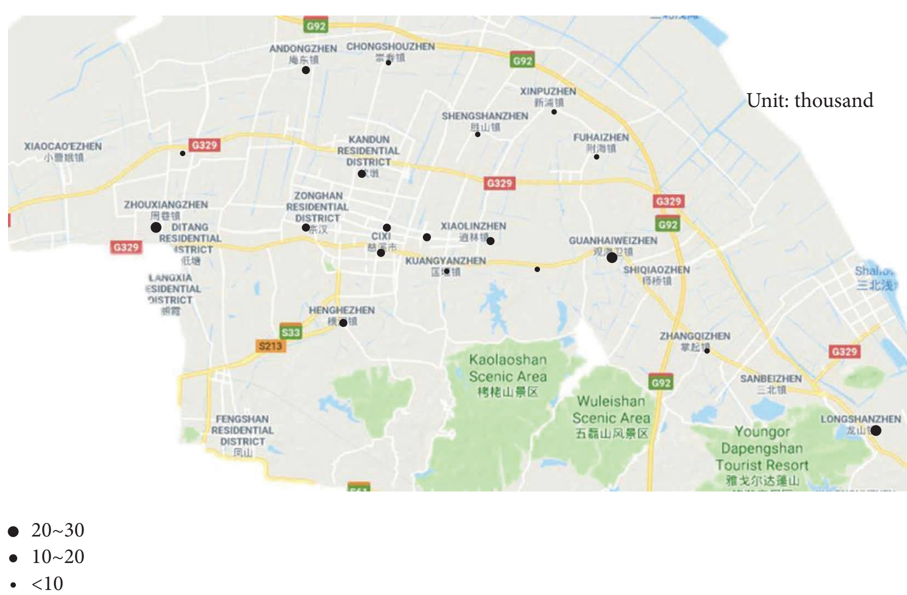

Figure 2: The map of Cixi.

Cixi City is consistent with the national average level, it is estimated that the number of EVs in Cixi City will be 0.136 million in 2030. According to the proportion of the population, the number of EVs in each region can be obtained, as shown in Table 3.

Take the forecast EV data of 2030 as the demand parameter. The coverage radius of the point demand is set to be 4 km. Figures 7–9 show the trends of covered point demands, covered path demands, and the objective values with the number of charging stations increasing under different θ.

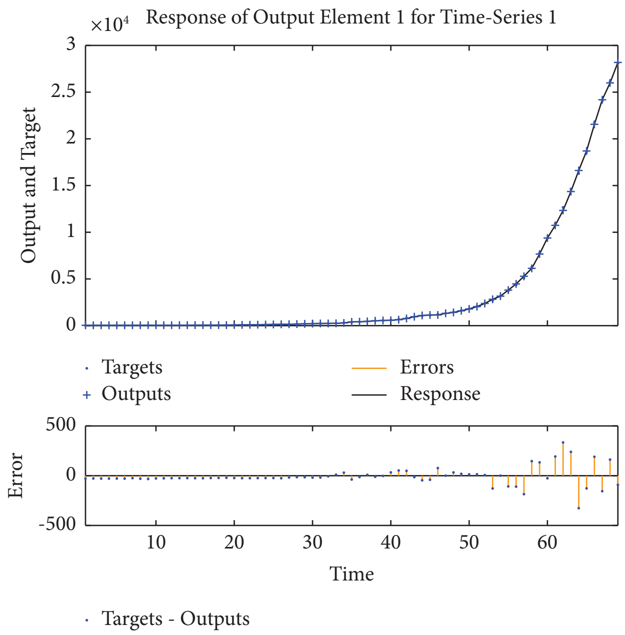

Figure 3: The error between the predicted national vehicle ownership data and the actual data.

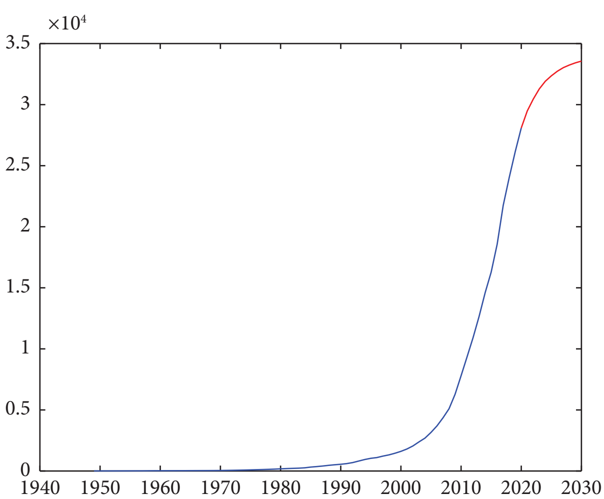

Figure 4: Forecast of vehicle ownership quantity in China.

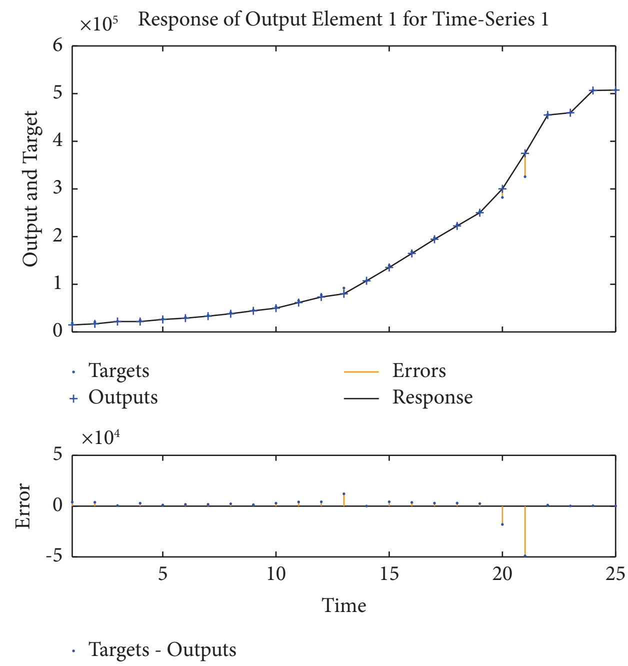

Figure 5: The error between the predicted car ownership data and the actual data in Cixi City.

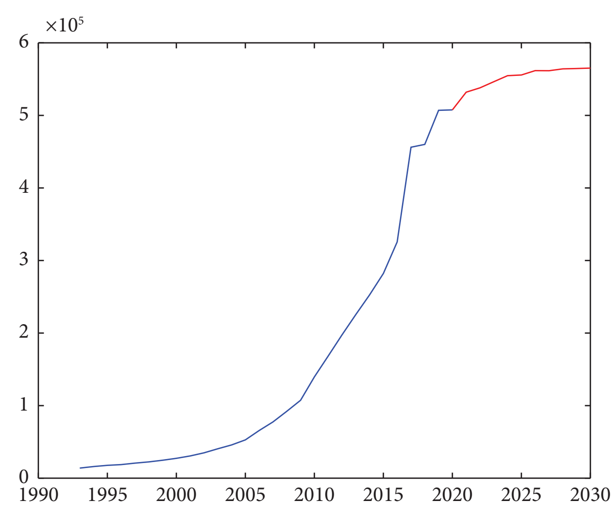

Figure 6: Forecast of vehicle ownership quantity in Cixi.

As we know, in traditional maximum coverage location problems and FILP, the objective is a convex function of the number of facilities. However, with the experiments of different θ, we find that the covered point and path demands have no convexity property with the number of charging stations in our model because of the trip mileage limit.

Figure 10 shows the impact of θ on the location decision. We considered two extreme cases, $\theta = 0$ and 1. When $\theta = 0$, the model is transformed into FILP with the trip mileage limit. When $\theta = 1$, the model is just the maximum coverage model. Compared with the only consideration being the point demand ($\theta = 1$) or flow demand ($\theta = 0$), what is the difference in charging station location when considering both demands? We set the number of charging stations at 5. Figure 10 shows the location decisions with consideration of only point demand, only flow demand, and both types of demands ($\theta = 0.1$). When only the point demand is considered, the layout of the charging station is relatively scattered. Although the demand for point 19 (Longshanzhen) is large, it is relatively remote and far away from other areas. Building the charging station at point 19 makes the station more isolated and unable to enter the effective mileage endurance network. When only the flow demand is considered, the charging stations are set up intensively, mainly in the urban area. Although it is convenient for residents to travel in the urban area, this setting is not ideal for properly expanding the service network, and it is inconvenient for rural areas. When set $\theta = 0.1$, we found that the solution balances the above contradictions. The charging

Table 3: Forecast of EV ownership quantity in each region.

Point	Region	Forecast quantity
1	Zhouxiangzhen	28216
2	Changhezhen	7979
3	Andongzhen	13533
4	Zhonghan district	13985
5	Hushan district	19279
6	Gutang district	13081
7	Baisha district	11705
8	Kandun district	11420
9	Congshouzhen	6342
10	Henghezhen	11641
11	Kuangyanzhen	5831
12	Qiaotouzhen	8567
13	Xiaolinzhen	10019
14	Shengshanzhen	6918
15	Xinpuzhen	8821
16	Fuhaizhen	5548
17	Guanhaiweizhen	24607
18	Zhangqizhen	9373
19	Longshanzhen	20136

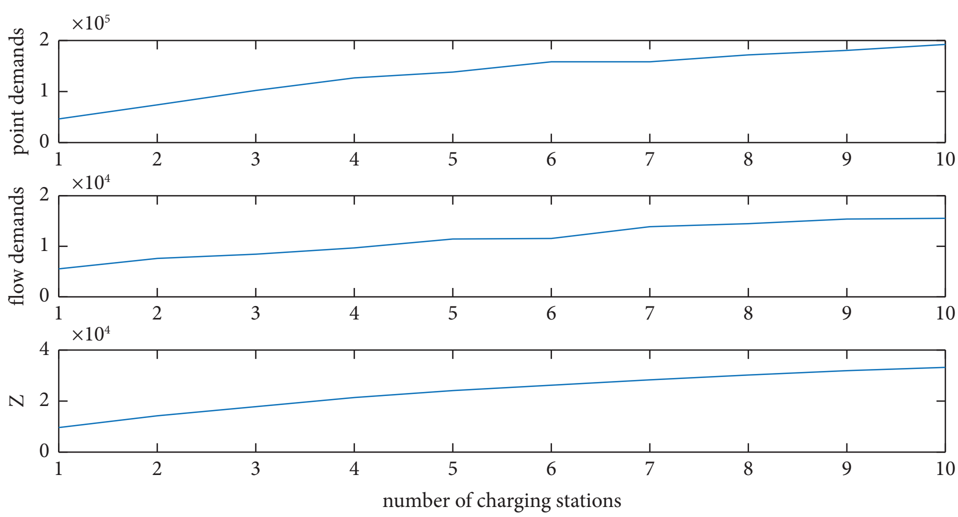

Figure 7: Covered point demands and covered path demands and the objective values with the number of charging stations increasing under $\theta = 0.1$.

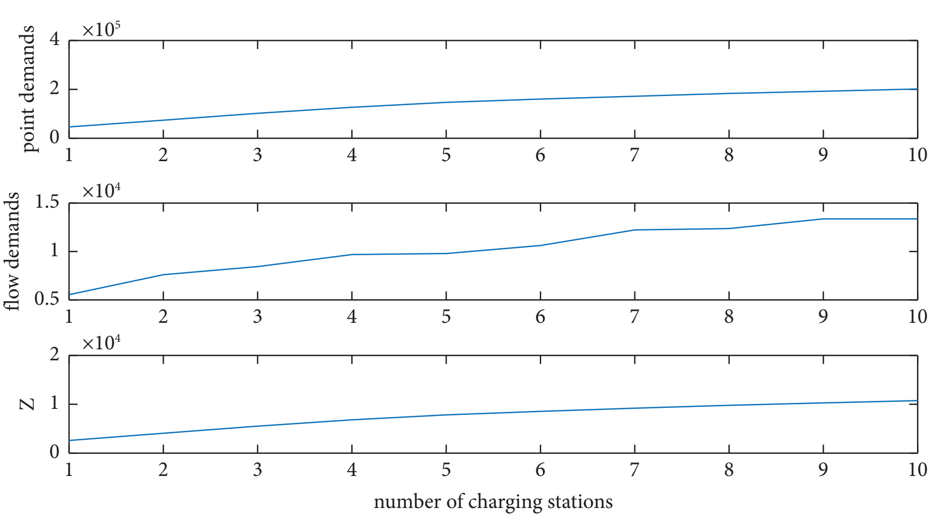

Figure 8: Covered point demands and covered path demands and the objective values with the number of charging stations increasing under $\theta = 0.5$.

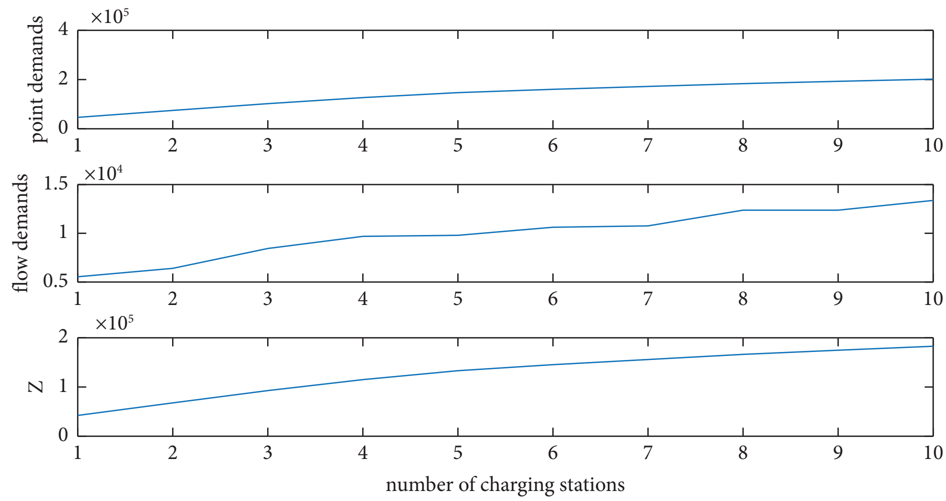

Figure 9: Covered point demands and covered path demands and the objective values with the number of charging stations increasing under $\theta = 0.9$.

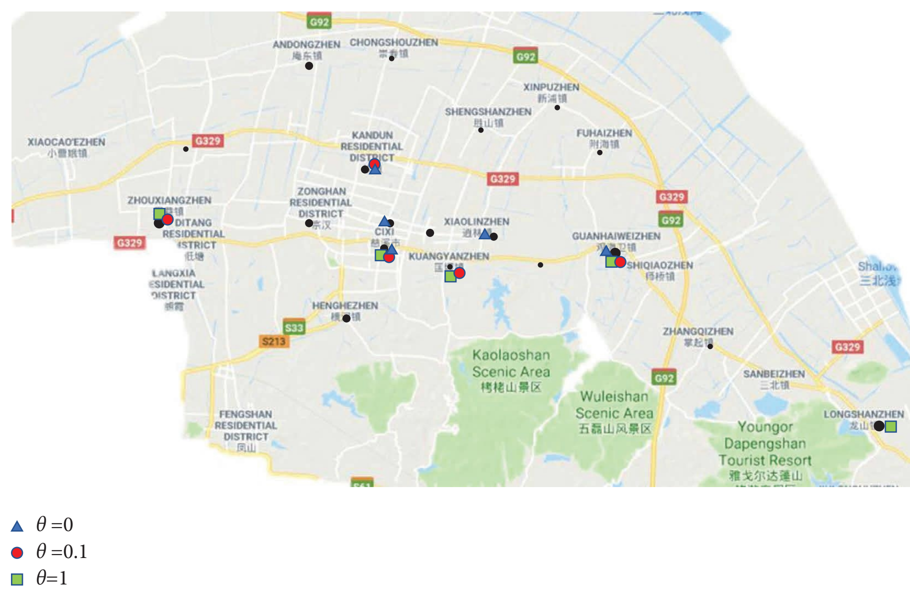

Figure 10: Influence of θ on location results.

station location is neither too centralized nor remote or isolated so as to ensure the coverage and appropriate extension of the charging network.

6. Conclusion

This paper studies the location of EV charging stations considering both point and path charging demands. Demands are closely related to the EV number. So, the location of the charging station largely depends on the data of EV numbers. As the fast expansion of EVs, the current number of EVs is not a solid basis for the design of charging stations because after the stations finish, the number of EVs has changed greatly. This paper proposes a prediction method for EV numbers with a neural network. Then, through SIM, we obtain the future path demand between each O-D pair. As range anxiety is one of the main concerns for consumers buying EVs, the trip mileage limit is considered in our model. Then we propose a greedy algorithm to solve our model. It is found that the solution accuracy of the algorithm is verified to be related to the value of the mileage limit by using random examples. The smaller the trip mileage limit, the greater the gap between the computational result and the precise solution. Finally, through a case study, we find that the location decision is shown to be more reasonable with our model than with the maximum coverage model or FILP. Our method ensures the coverage and appropriate extension of the charging network.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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