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Location of Electric Vehicle Charging Piles Based on Set Coverage Model

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Abstract: Electric vehicles are rapidly popping up in the market as a new alternative to fossil fuels, in order to reduce carbon emissions in urban areas. However, the improper placement of charging piles has impeded the development of electric vehicles. In this paper, 12 indicators from 4 categories, namely economy, environment, cost, and service quality are selected to form an index system for evaluating the location of electric vehicle charging piles. The entropy weight-TOPSIS method is also applied for the same purpose. On the basis of the evaluation, this paper proposes a set coverage model and adopts a greedy heuristic algorithm to find out the optimal location of charging piles. Finally, the paper verifies the reasonability and feasibility of this model by studying the existing location of electric vehicle charging piles in northeast China. The evaluation is based on the Liaoning Province Electric Vehicle Big Data Supervision Platform, which has data that are official and scientifically based. The set coverage model proposed, based on the evaluation, is a new solution to finding out the optimal location of electric vehicle charging piles across China. This study aims to provide a theoretical basis for the development of this new energy industry.

Keywords: electric vehicles; charging piles; entropy weight-TOPSIS; set coverage model

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1. Introduction

In this new era, it is necessary to promote a green and low-carbon life. With policy dividend and technology advancement, China's electric vehicle industry is booming with remarkable results achieved. As of January 2020, more than 3.85 million electric vehicles have been manufactured and 531,000 public charging piles have been installed in China [1]. Northeast China is a region where the development of electric vehicles has set off to a good start. In this region, the task of controlling haze is still demanding, and much infrastructure development is underway. Therefore, there exists the need for environmental protection, energy conservation, and emissions reduction, unleashing the development potential of new industries to revitalize the region and upgrade its industrial structure. Since the industrial revolution, fossil energy has been the main source of energy for propelling cars. Although this has contributed much to the economy and brought convenience to people's lives, it has led to a cascade of environmental problems, due to combustion. The electric vehicle is more eco-friendly compared to traditional cars, as it is the electricity stored in the battery pack that propels the vehicle, without producing exhaust gases. For this reason, developing electric vehicles has become a key national strategy, especially in cities facing daunting tasks to control haze. Against such a backdrop, it is imperative to install more charging piles in order to meet the demand for charging electric vehicles.

However, critical issues have presented themselves: some electric vehicles currently have nowhere to charge, or charging piles in some places are left unused. The improper location of charging piles impedes the development of electric vehicles. Therefore, for the electric vehicle industry to boom, properly situating charging piles is the first step to take.

After reviewing previous papers, this study decided to focus on two aspects: one is to evaluate the location of electric vehicle charging piles, and the other is to discuss how to properly situate charging piles. It was found that many studies by domestic and foreign researchers focused on the former topic, with special attention given to the evaluation index system and the choosing of evaluation methods. Guo S et al. [2–4] built a sustainable index system for evaluating the location of electric vehicle charging piles, which included environmental, economic, and social factors. Cao et al. [5,6] summarized factors that influenced the location of charging piles. Ren Q L et al. [7–9] took six factors into account and created an index system including traffic, environment, electricity, planning, land, and cost. Wang J Y et al. [10–12] determined evaluation indicators from four categories: easy transportation, cost-effective operation, grid safety, and contribution to district economy. Zhou Y T et al. [13,14] used a hierarchical analysis to identify four influencing factors: safety, population, location, and traffic. As the location of the logistics distribution center was key to its operation, Qin L et al. [15–17] put in place an index system for evaluating the location of logistics distribution centers from the perspective of natural conditions, business environment, infrastructure, and cost. Um S et al. [18] built an evaluation index system covering four aspects: safety, economy, environment, and operation, in order to find out the most desirable location of substations. He Y H et al. [19] developed an index system for evaluating the location of airport fire stations from five categories: time to rescue location, congestion, probability of occurrence, operational risk, and coordination with other institutions.

As for the choosing of evaluation methods, Chen J H et al. [20] drew lessons from the comprehensive index system for evaluating thermal power plant engineering, determined the weight of each evaluation indicator through hierarchical subdivision method, and established a fuzzy comprehensive evaluation model. While taking into account the features of the coal industry, Zhang S et al. [21] shed light on the evaluation method from the perspective of district planning to complement enterprise and customer service, and conducted a hierarchical analysis on the location of typical coal logistics nodes in Shaanxi Province. Hua Y P et al. [22] combined Delphi method and gray hierarchical analysis, and proposed a new comprehensive location evaluation method. Cases applied with such a method proved its feasibility. Given that there was much uncertainty in choosing the location of parks, Dai H et al. [23–25] used a hierarchical analysis to build an evaluation index system, and used the fuzzy comprehensive evaluation method to evaluate the location of logistics parks. Tao et al. [26–28] created a mathematical model using genetic algorithm of Matlab software. Wei et al. [29,30] performed fuzzy multi-objective decision making by combining weighted fuzzy TOPSIS and gray relational analysis. The proper location of substations is significant to the power system, and Guler et al. [31–33] applied a hierarchical analysis and a fuzzy hierarchical analysis to evaluate the location of substations. Alao M A et al. [34] proposed a novel hybrid multi-criteria approach based on IDOCRIW and TOPSIS, considering 14 criteria, including technical, economic, environmental, and social factors.

Building charging piles is crucial to the development of electric vehicles, and the proper location of charging piles can not only increase the use of electric vehicles, but also reduce cost in construction, operation, and maintenance. Among studies on how to place charging piles properly, Efthymiou et al. [35–37] studied the location of the charging facilities in Thessaloniki city using a genetic algorithm. Wang Y et al. [38] developed a multi-objective decision model aiming at maximizing traffic flow and minimizing network loss with a Freudian algorithm. Qin Z J et al. [39–41] subdivided the cost into electricity cost, fixed travel cost of a vehicle, opportunity cost, and penalty cost. They built a model for choosing the proper location of charging stations with the purpose of minimizing the total cost, and proposed an improved genetic algorithm. Pan M Y et al. [42] developed a set coverage model with an objective function, the goal of which was to cover the widest areas with the least charging stations and the lowest cost. They combined a greedy algorithm and an entropy power method to work out the solution of this model.

From what is discussed above, it can be seen that most of the existing studies focus more or less on the location of electric vehicle charging piles. But few use an index system to evaluate the location systematically, which is exactly the focus of the government and the market. Therefore, this paper evaluates the location of charging piles in northeast China from four aspects: economy, environment, cost, and service quality. Combining the entropy weight method and TOPSIS method, this paper evaluates the location of charging piles based on the set coverage model while considering the situation of each province. The rationality and feasibility of this model are verified. The data used by this paper are sourced from the Liaoning Province Electric Vehicle Big Data Supervision Platform, which is official but not released. This paper also studies the proper location of charging piles using a scientifically based model to make the choosing of location more targeted and reasonable.

2. The Index System for Evaluating the Location of Electric Vehicle Charging Piles

The charging pile is the supporting facility for electric vehicles. It is composed of a body, an electrical module, a metering module, and so on. Currently, there are three modes for charging electric vehicles: quick charging, slow charging, and battery swapping. The slow charging mode is the most widely used. According to surveys, 90% of vehicles are charged this way, while those with quick charging is less than 10%.

2.1. Building the Index System for Evaluating the Location of Charging Piles

On the basis of previous studies, this paper summarizes several factors influencing the location of electric vehicle charging piles. To be objective and reasonable, while considering data availability, 12 indicators are selected from four categories, including economy, environment, cost, and service quality. These indicators constitute the index system for evaluating the location of electric vehicle charging piles. According to personal experience, more indicators are added: C_1, C_2, C_{10}. The index system is shown in Table 1.

Table 1. The index system for evaluating the location of electric vehicle charging piles.

First-Level Indicators	Second-Level Indicators	Indicator Attribute	Source of Indicator	Source of Data
B_1: economy	C_1: gross district product	Positive		Statistical yearbook
	C_2: fiscal revenue	Positive		
	C_3: per capita disposable income	Positive	Wang J Y (2018) [10] and so on	
B_2: environment	C_4: population	Positive	Wang J Y (2018) [10], Wan X H (2020) [13] and so on	
	C_5: land area	Positive	Zhang J (2018) [11] and so on	
	C_6: population density within an area	Positive	Yao L (2015) [8] and so on	
B_3:cost	C_7: land price	Negative	Xiang H (2019) [12] and so on	Bureau of Natural Resources
	C_8: construction cost	Negative	Wang J Y (2018) [10], Xiang H (2019) [12] and so on	The questionnaire survey
	C_9: operatiion cost	Negative		
B_4: service quality	C_{10}: the number of charging piles	Positive		China Liaoning Electric vehicle big data supervision platform
	C_{11}: utilization	Negative	Wei L (2016) [9] and so on	
	C_{12}: charging price	Negative	Wu H F (2020) [14] and so on	

Note: Indicators C_1, C_2, and C_{10} are added according to personal experience.

The index system developed in this paper includes both quantitative and qualitative indicators, among which nine indicators from economy, environment and service quality, and the land price under the cost factor are quantitative, while the construction cost and the operation cost under the cost factor are qualitative, because it is difficult to weigh them by number. The questionnaire is used to evaluate quantitative factors. The result of the study can provide a theoretical basis for choosing the location of charging piles.

2.2. Entropy Method

There are many evaluation methods, such as the hierarchical analysis, the gray correlation method, and the data envelopment method, etc. The entropy weight method, which is objective, works by calculating the entropy weight of each indicator through the information entropy, and on this basis, ranking the weight of all indicators to obtain a more objective weight for each indicator [2]. After the weight of indicator is determined, the TOPSIS method is applied to solve the problem of the multi-objective decision. The evaluation on the location of charging piles is made in an objective way to avoid errors caused by subjective assumption. The result of which sheds light on finding out the optimal location for electric vehicle charging piles.

(1) Develop the original evaluation index matrix. The original matrix forms evaluation schemes and n indicators as follows:

$$A = \left(a_{ij}\right)_{m\times n} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix} \tag{1}$$

In the formula: a_{ij} is the jth indicator value of the ith evaluation scheme.

(2) Standardize the data in the matrix with the following equation.

For positive indicators:

$$X_{ij} = \frac{a_{ij} - a_j^{\min}}{a_j^{\max} - a_j^{\min}} \tag{2}$$

For negative indicators:

$$X_{ij} = \frac{a_j^{\max} - a_{ij}}{a_j^{\max} - a_j^{\min}} \tag{3}$$

(3) Normalize matrix A.

$$A_{ij} = \frac{X_{ij}}{\sum\limits_{i=1}^{m} X_{ij}} \tag{4}$$

The normalized matrix A^* is obtained:

$$A^* = \left(X_{ij}\right)_{m\times n} = \begin{pmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{pmatrix} \tag{5}$$

(4) Calculate the information entropy.

$$H_j = -k\sum_{i=1}^{m} X_{ij} \ln X_{ij}, j = 1, 2, \cdots, n \tag{6}$$

In the formula: $k = \frac{1}{\ln m}$, $k > 0$, $H_j \leq 1$.

(5) Calculate the entropy weight.

$$w_j = \frac{1 - H_j}{\sum\limits_{j=1}^{m} \left(1 - H_j\right)} \tag{7}$$

Among them, $0 \leq w_j \leq 1$, $\sum_{i=1}^{m} w_j = 1$, w_j represents the weight coefficient of indicator j, and $1 - H_j$ represents the difference coefficient of indicator j.

2.3. TOPSIS Method

The TOPSIS method, also known as the Technique for Order of Preference by Similarity to Ideal Solution, is a common, multi-criteria decision analysis method for finite solutions, which mainly relies on the "ideal solution" and "negative ideal solution" of the decision problem to do the ranking and choose the optimal solution. TOPSIS needs to be processed in a weighted, normalized decision matrix. As indicators have different dimensions, it is necessary to normalize the original data.

(1) Develop the normalized decision matrix Z = $(Z_{ij})_{m\times n}$:

$$Z_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}{}^2}} \quad j = (1, 2, \cdots, n) \tag{8}$$

Develop the weighted normalized decision matrix V, element V_{ij} = $W_j Z_{ij}$, where w_j represents the weight coefficient of indicator j.

(2) Determine the ideal solution and the negative ideal solution.

The larger the value of element V_{ij} in the decision matrix V, the better the scheme is.

Ideal solution:

$$V^{+} = (V_1^{+}, V_2^{+}, \cdots, V_m^{+}) = \{\max V_{ij} | j = 1, 2, \cdots, m\} \tag{9}$$

Negative ideal solution:

$$V^{-} = (V_1^{-}, V_2^{-}, \cdots, V_m^{-}) = \{\min V_{ij} | j = 1, 2, \cdots, m\} \tag{10}$$

(3) Calculate the distance from each scheme to the ideal $S_i{}^{+}$ and the distance from each scheme to the negative ideal $S_i{}^{-}$.

$$S_i^{+} = \sqrt{\sum_{j=1}^{m} (V_j{}^{+} - V_{ij})^2} \tag{11}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{m} (V_j{}^{-} - V_{ij})^2} \tag{12}$$

(4) Calculate the relative proximity of each scheme.

$$C_i = \frac{S_i}{S_i^{+} + S_i^{-}} \tag{13}$$

Rank the result by relative proximity. The larger the value of C_i, the better the overall performance.

3. An Optimal Model for Choosing the Location of Charging Piles Based on Location Evaluation

Choosing the location by coverage is one of the three typical models for choosing the location. This was first put forward by Toregas and other scholars. This model is mainly used to choose the location for emergency service facilities, which requires the widest coverage with the least number of service facilities [43].

3.1. Model Overview

The set coverage model functions by distributing discrete points. When the demand points are given, a set of service points can be determined to meet the demand and cover all demand points with the least number of service store areas. The model is often applied to logistics distribution centers, express delivery outlets, gas stations, emergency centers, and electric vehicle charging piles. M refers to the set of candidate points, $M = \{1, 2, \cdots, m\}$; N is the set of demand points, $N = \{1, 2, \cdots, n\}$ (By researching map information and related literature, the crowd flow center is selected and N is taken as the demand point for charging piles); x_i represents whether to set up a charging pile at point i, and when:

$$x_i = \begin{cases} 1, \ \textit{The charging pile is located at point i} \\ 0, \ \textit{The charging pile is not located at point i} \end{cases} \tag{14}$$

r_{ij} is the distance from candidate point i to demand point j, R is the warning distance that the electric vehicle can run with the electricity left, and y_{ij} represents whether point j is within the range of point i. x_i is the node, y_{ij} is 1 when it is selected, and 0 when it isn't. To be specific, if the distance between the vehicle and candidate point j is smaller than that between the vehicle and demand point i, y_{ij} is 1, otherwise it is 0.

$$y_{ij} = \begin{cases} 1, r_{ij} \leq R \\ 0, r_{ij} > R \end{cases} \tag{15}$$

The objective function is as follows (The objective function of the set coverage model refers to the number of demand points covered within the alarm-driving distance of the candidate points, so that the construction cost is minimized):

$$\min \sum_{i=i}^{m} X_i \tag{16}$$

$$s.t \begin{cases} \sum\limits_{i=1}^{m} x_i y_{ij} \geqslant 1 \\ x_i = 0 \ or \ 1 \\ y_{ij} = 0 \ or \ 1 \\ i \in M, j \in N \end{cases} \tag{17}$$

3.2. Model Solution

First, demand points and candidate points of electric vehicle charging piles are determined according to the distribution of existing charging piles in each district. Since the set coverage model is an NP-hard problem with polynomial complexity, this paper, based on the 0–1 programming model and following the greedy algorithm, has obtained the optimal solution on MATLAB software.

4. Case Application

4.1. Background

City S is located in the south of Northeast China, and at the center of the Northeast Asian Economic Circle and the Bohai Rim Economic Circle. It is a comprehensive hub connecting the Yangtze River Delta, the Pearl River Delta, and Beijing-Tianjin-Hebei District to Northeast China. In 2020, the total gross domestic product (GDP) of city S reached 657.16 billion yuan, up 0.8% from the previous year. In the innovation-driven era, with electric-driven vehicles the main focus of national strategy, the new path to developing the electric vehicle industry in a fast, efficient, healthy, and sustainable way lies in properly placing charging stations and other infrastructure within overall planning.

4.2. Evaluation on the Location of Charging Piles

First, demand points of this paper are located in ten districts of city S.

(1). Data collection and processing.

After collecting the data for each indicator, we analyzed the economic, environmental, cost, and service quality factors. The initial data for different indicators were obtained from the statistical yearbook, the Bureau of Natural Resources, the Bureau of Statistics, and the Liaoning Province Electric Vehicle Big Data Supervision Platform, as shown in Table 2.

Table 2. Charging facilities by district in City S.

District	Number of Charging Stations	Number of Charging Piles	Number of Charging Ports	Number of Charging Ports Used	Number of Unused Charging Ports	Utilization Rate
D1	10	57	57	19	38	33.33%
D2	5	32	32	22	10	68.75%
D3	6	54	84	73	11	86.90%
D4	2	6	6	6	0	100%
D5	3	28	28	12	16	42.86%
D6	2	28	28	20	8	71.43%
D7	9	128	128	72	56	56.25%
D8	6	59	59	54	17	91.53%
D9	4	29	29	25	4	86.21%
D10	1	12	12	11	1	91.37%

Note: D1~D10 represent the first~tenth district respectively.

As the data about the construction cost and the operation cost were limited, they went through processing. The questionnaire was used with the value of data made between 0 and 1. The land price, construction cost, operation cost, utilization rate, and charging price were negative indicators. After the questionnaire was analyzed, we developed the Table 3 showing indicators.

Table 3. Initial data required for the evaluation of indicators.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
C_1	947.2	965.5	776.6	564.1	982.3	227.2	546	373.4	364.4	189.3
C_2	91.1	79.3	84.6	37.5	118.5	23.9	87.5	40.6	38.1	8.6
C_3	52,852	52,510	47,854	47,379	47,373	37,527	49,158	42,273	48,681	36,908
C_4	74.4	72	63.8	84.6	98.7	42.5	44.6	34.3	46.9	51
C_5	59	60	100	66	286	782	734	884	499	1645
C_6	12,608	11,998	6380	12,812	3449	544	608	388	939	310
C_7	2441	2441	2441	1826	1419	358	944	324	706	581
C_8	0.18	0.18	0.18	0.14	0.11	0.03	0.07	0.02	0.05	0.04
C_9	0.96	0.56	0.20	0.14	0.26	0.04	0.36	0.08	0.09	0.01
C_{10}	7	3	6	2	3	2	9	6	4	1
C_{11}	33.33	68.75	86.9	100	42.86	71.43	56.25	91.53	86.21	91.37
C_{12}	0.76	0.76	0.77	0.94	0.76	0.78	0.76	0.78	0.76	0.78

Note: D1~D10 represent the first~tenth district respectively.

(2). Calculate the information entropy and the weight of various indicators.

The information entropy and weight of the 12 indicators were calculated following Formulas (1)–(7), as shown in Table 4.

Table 4. The information entropy and the weight of each indicator.

Index	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Information entropy	0.862	0.890	0.898	0.869	0.732	0.704	0.818	0.813	0.943	0.866	0.855	0.954
Weights	0.077	0.061	0.057	0.073	0.149	0.164	0.101	0.104	0.032	0.074	0.081	0.026

(3). Calculate the distance between positive and negative ideal solutions.

The distances between the 10 districts and the positive and negative ideal solutions were calculated following Formulas (8)–(13), as shown in Table 5.

Table 5. The distances between the 10 districts and the positive and negative ideal solutions.

District	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
S_i^+	0.109	0.112	0.117	0.117	0.123	0.135	0.120	0.129	0.135	0.123
S_i^-	0.121	0.113	0.088	0.106	0.066	0.051	0.068	0.064	0.041	0.108

Note: D1~D10 represent the first to the tenth district respectively.

(4). Calculate the proximity.

The proximity of the 10 districts in City S was calculated following Formula (13), as shown in Table 6.

Table 6. The proximity of each district.

District	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Proximity	0.5254	0.5029	0.4284	0.4758	0.3484	0.2720	0.3620	0.3319	0.2335	0.4670

Note: D1~D10 represent the first~tenth district respectively.

(5). The location evaluation results.

The proximity of the 10 districts of S city was calculated, as shown in Figure 1. The proximity was in the following sequence from highest to lowest: district 1, district 2, district 4, district 10, district 3, district 7, district 5, district 8, district 6, and district 9.

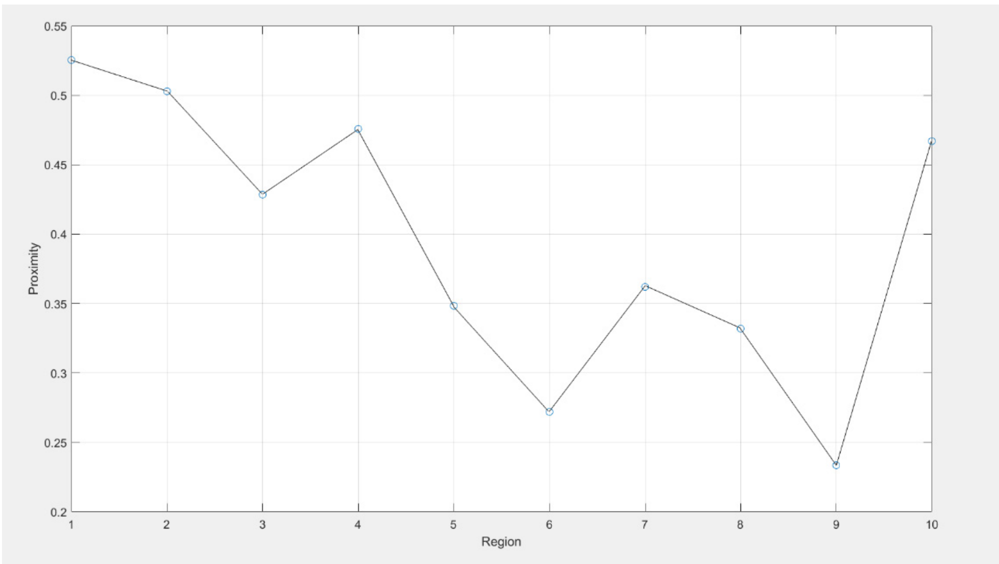

Figure 1. The proximity of each district.

4.3. Optimal Location for Charging Piles

According to the district's urgency to choose the location for charging piles, the paper selected the top three districts from the location evaluation results: district 1, district 2, and district 4, to find the optimal location, which would be significant to the overall planning of the location for charging piles.

(1). Current distribution of charging piles.

We know the location of electric vehicle charging piles in district 1, 2, and 4 from the China Liaoning Province Electric Vehicle Big Data Supervision Platform. The latitude and longitude of 10 candidate points are shown in Table 7.

Table 7. Coordinates of candidate points.

Candidate Points	Name of the Charging Station	Latitude and Longitude (X, Y)
X_1	Fast Charging Station of the Power Supply Company in the Subcenter of the First District of City S	123.41445, 41.788826
X_2	Fast Charging Station in the Parking Lot of the Power Supply Company in City S	123.41351, 41.78819
X_3	Charging Station in the Power Supply Business Hall S in the First District of City S	123.37849, 41.763702
X_4	Charging Station in the Power Supply Business Hall X in the First District of City S	123.40962, 41.808136
X_5	Charging Station in the Power Supply Business Hall C in the First District of City S	123.39387, 41.740097
X_6	Charging Station on Road Z in the First District of City S	123.36247, 41.71956
X_7	Charging Station in the Power Supply Business Hall Z in the First District of City S	123.43168, 41.770733
X_8	Charging Station in the Car Rental Company in City S	123.48667, 41.767483
X_9	Electric vehicle public fast charging station in S city Charging Station in the Parking Lot of the Washington Square in the Second District City S	123.436676, 41.8116
X_{10}	Charging Station on Road Wenyi in the Second District City S	123.4558, 41.7779
X_{11}	Charging Station in the Power Supply Business Hall in the Fourth District of City S	123.40768, 41.82042
X_{12}	Charging Station in Nujiang Power Supply Business Hall in the Fourth District of City S	123.3838, 41.826805

By checking the map and reviewing relevant literature, we chose 16 places with high traffic as demand points for charging piles, as shown in Table 8.

Table 8. Coordinates of demand points.

Demand Point	Longitude and Latitude (X, Y)	Demand Point	Longitude and Latitude (X, Y)
Y_1	123.353662, 41.70986	Y_9	123.432386, 41.821043
Y_2	123.442238, 41.756343	Y_{10}	123.46856, 41.808196
Y_3	123.425494, 41.774437	Y_{11}	123.539312, 41.81859
Y_4	123.396867, 41.786684	Y_{12}	123.573367, 41.821507
Y_5	123.388137, 41.705164	Y_{13}	123.515103, 41.787712
Y_6	123.372811, 41.743452	Y_{14}	123.45959, 41.775882
Y_7	123.40536, 41.797148	Y_{15}	123.43753, 41.831327
Y_8	123.41823, 41.810196	Y_{16}	123.439101, 41.870088

The distance between the location of the candidate points and the demand points can be seen in Figure 2.

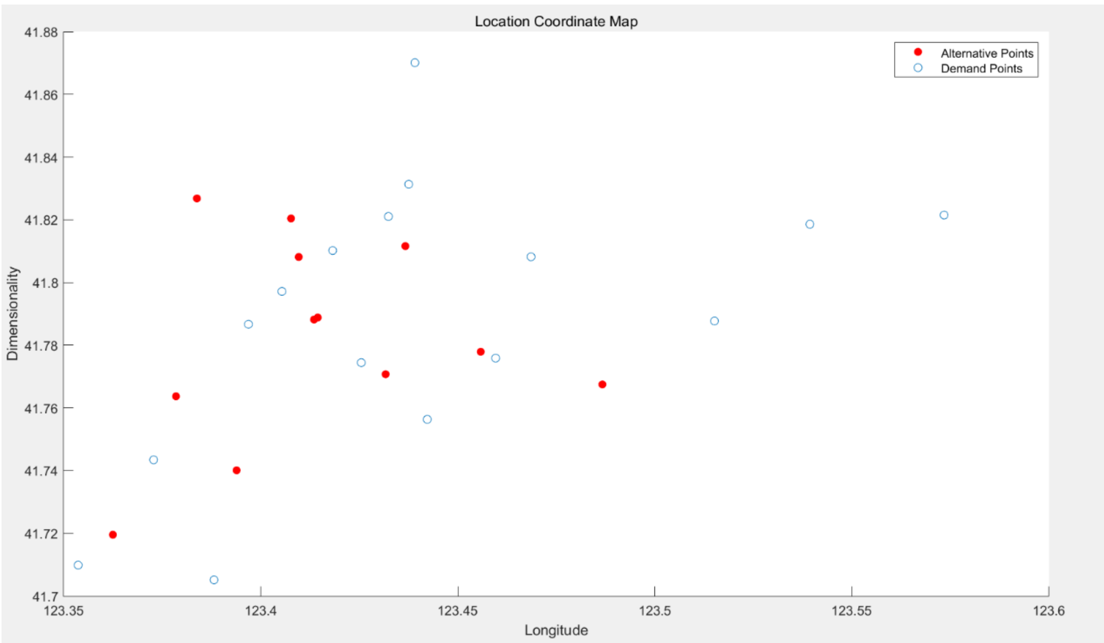

Figure 2. Coordinates of candidate points and demand points.

(2). Analyzing the Set Coverage Model.

From relevant literature, it is known that an electric vehicle can drive no more than 3 km after a power-off warning is sent out. Therefore, the maximum driving distance was set to 3 km. Based on this, we further analyzed the candidate points in Figure 2 and obtained the demand points covered within the radius of 3 km for each candidate point, as shown in Table 9.

Table 9. Candidate points and their coverage areas.

Candidate Point	Demand Points Covered within the Radius of 3 km	Candidate Point	Demand Points Covered within the Radius of 3 km
X_1	X_2, X_4, X_7, Y_3, Y_4, Y_7, Y_8	Y_3	X_1, X_2, X_3, X_7, Y_2, Y_4, Y_7
X_2	X_1, X_4, X_7, Y_3, Y_4, Y_7, Y_8	Y_4	X_1, X_2, X_3, Y_3, Y_7
X_3	X_5, Y_3, Y_4, Y_6	Y_5	X_6
X_4	X_1, X_2, X_9, X_{11}, Y_7, Y_8, Y_9, Y_{15}	Y_6	X_3, X_5, X_6
X_5	X_3, Y_6	Y_7	X_1, X_2, X_4, Y_3, Y_4, Y_8
X_6	Y_1, Y_5, Y_6	Y_8	X_{10}, Y_{13}, Y_{14}
X_7	X_1, X_2, X_{10}, Y_2, Y_3, Y_{14}	Y_9	None
X_8	X_{10}, Y_{14}	Y_{10}	X_9, X_{10}
X_9	X_4, X_{11}, X_{15}, Y_8, Y_9, Y_{10}	Y_{11}	Y_{12}
X_{10}	X_7, X_8, Y_{10}, Y_{14}	Y_{12}	Y_{11}
X_{11}	X_4, X_9, X_{12}, Y_8, Y_9, Y_{15}	Y_{13}	X_8
X_{12}	X_{11}	Y_{14}	X_7, X_8, X_{10}, Y_2
Y_1	X_6	Y_{15}	X_4, X_9, X_{11}, Y_8, Y_9
Y_2	Y_3, Y_{14}	Y_{16}	None

Note: There is no coverage demand point within the radius of 3 km for candidate points Y_9 and Y_{16}.

According to the constraint in Equation (17) and the coverage areas in Table 9, we can obtain the constraint function:

$$\begin{cases}
X_1 + X_2 + X_4 + X_7 + Y_3 + Y_4 + Y_7 + Y_8 \geq 1 \\
X_3 + X_5 + Y_3 + Y_4 + Y_6 \geq 1 \\
X_1 + X_2 + X_4 + X_9 + X_{11} + Y_7 + Y_8 + Y_9 + Y_{15} \geq 1 \\
X_3 + X_5 + Y_6 \geq 1 \\
X_6 + Y_1 + Y_5 + Y_6 \geq 1 \\
X_1 + X_2 + X_7 + X_{10} + Y_2 + Y_3 + Y_{14} \geq 1 \\
X_8 + X_{10} + Y_{14} \geq 1 \\
X_4 + X_9 + X_{11} + X_{15} + Y_8 + Y_9 + Y_{10} \geq 1 \\
X_7 + X_8 + X_{10} + Y_{10} + Y_{14} \geq 1 \\
X_4 + X_9 + X_{11} + X_{12} + Y_8 + Y_9 + Y_{15} \geq 1 \\
X_{11} + X_{12} \geq 1 \\
X_6 + Y_1 \geq 1 \\
X_7 + Y_2 + Y_3 + Y_{14} \geq 1 \\
X_1 + X_2 + X_3 + X_7 + Y_2 + Y_3 + Y_4 + Y_7 \geq 1 \\
X_1 + X_2 + X_3 + Y_3 + Y_4 + Y_7 \geq 1 \\
X_6 + Y_5 \geq 1 \\
X_3 + X_5 + X_6 + Y_6 \geq 1 \\
X_1 + X_2 + X_4 + Y_3 + Y_4 + Y_7 + Y_8 \geq 1 \\
X_{10} + Y_8 + Y_{13} + Y_{14} \geq 1 \\
X_9 + X_{10} + Y_{10} \geq 1 \\
X_9 + X_{10} + Y_{10} \geq 1 \\
Y_{11} + Y_{12} \geq 1 \\
X_8 + Y_{13} \geq 1 \\
X_7 + X_8 + X_{10} + Y_2 + Y_{14} \geq 1 \\
X_4 + X_9 + X_{111} + Y_8 + Y_9 + Y_{15} \geq 1
\end{cases}$$

(3). Optimal location.

The constraint function was worked out according to Formulas (16) and (17), and obtained the least number of candidate points that could cover all demand points. Given that there was much calculation to be done, we ran the greedy heuristic algorithm on Python software. The final results are shown in Table 10.

Table 10. The optimal location of candidate points.

Candidate Point	Longitude and Latitude	District
X_3	123.37849, 41.763702	D1
X_4	123.40962, 41.808136	D1
X_6	123.36247, 41.71956	D1
X_8	123.48667, 41.767483	D2
X_9	123.436676, 41.8116	D2
X_{11}	123.40768, 41.82042	D4
Y_6	123.372811, 41.743452	D1
Y_8	123.41823, 41.810196	D1
Y_{11}	123.539312, 41.81859	D2
Y_{12}	123.573367,41.821507	D2
Y_{14}	123.45959, 41.775882	D2

From the results in Table 10, it can be seen that:

a. Taking into account the location of the existing charging piles, there were 16 demand points for electric vehicle charging piles.

After checking the map and reviewing relevant literature, this paper found it necessary to place 16 electric vehicle charging piles in such crowded places as the commercial center, residential areas, and industrial areas. Through model analysis, it was found that 11 demand points, namely Y_1, Y_2, Y_3, Y_4, Y_5, Y_7, Y_9, Y_{10}, Y_{13}, Y_{15} and Y_{16}, could meet the existing charging demand. But some electric vehicle owners still had no place to charge their cars. To solve this problem, this paper tried to find out the optimal location for charging piles for the above-mentioned high traffic places.

b. Through some calculation, the study found that the current location for some charging piles might be improper. So, their location awaited adjustment.

A total of 12 electric vehicle charging piles were built in the three selected districts of city S. Among them, 7 were in district 1, distributed in Y_1~Y_7; 3 were in district 2, distributed in Y_8, Y_9 and Y_{10}; and 2 were in district 4, distributed in Y_{11} and Y_{12}. According to the set coverage model, and considering that the maximum driving distance of an electric vehicle after a power-off warning was sent out was 3 km, the following charging piles were found to meet the above basic conditions: X_3, X_4 and X_6 in district 1, X_8 and X_9 in district 2, and X_{11} in district 4. The rest could not meet the needs of the vehicle owners. To reduce the operation cost and improve the efficiency of the charging piles, X_1, X_2, X_5, X_7, X_{10}, X_{12} were suspended for use.

c. To meet the demand for charging, five new charging piles need to be placed.

Based on the greedy heuristic algorithm, to meet the charging demand of electric vehicle owners, new charging piles should be placed for Y_6 and Y_8 in district 1 of city S and Y_{11}, Y_{12} and Y_{14} in district 2.

The analysis on the location of charging piles through the set coverage model should focus on improving the utilization rate. To cover all demand points, 11 out of 28 candidate points were selected in this paper: X_3, X_4, X_6, X_8, X_9, X_{11}, Y_6, Y_8, Y_{11}, Y_{12}, Y_{14}. In district 1, X_3, X_4, and X_6 were kept while Y_6 and Y_8 were newly built. In district 2, X_8 and X_9 remained in use while Y_{11}, Y_{12}, and Y_{14} were newly built. In district 4, only X_{11} was left. These charging piles could cover all demand points without overlap or inadequacy.

5. Conclusions

Based on previous studies on electric vehicles and their charging facilities in China, this paper studies the location of electric vehicle charging piles by developing the entropy-

TOPSIS model and the set coverage model. City S in Liaoning Province is studied to verify the feasibility of the model with data sourced from the Liaoning Province Electric Vehicle Big Data Supervision Platform.

Major achievements of this paper are as follows.

(1) The location of electric vehicle charging piles should be reasonable and feasible. It is the trend of the era to develop electric vehicles and new energy to reduce urban carbon emissions. However, after studying the current situation of charging facilities and problems related to electric vehicles, it is found that some electric vehicles have nowhere to charge, or that charging piles in some places are left unused. Therefore, the improper location of charging piles impedes the development of electric vehicles.

(2) This paper develops a reasonable and scientifically based index system for evaluating the location of charging piles. As many factors influence the choice of location, this paper focuses on economic factors, environmental factors, cost factors, and service quality factors, and uses the entropy weight-TOPSIS method to evaluate the location. Compared to other approaches, this method is more objective, with simple calculations. Using existing data, it can obtain scientific evaluation results to meet the need of choosing the optimal location for electric vehicle charging piles.

(3) According to the traffic and land conditions, this paper proposes the optimal location of charging piles by developing a set coverage model with city S as an example. An objective function is set up with known constraints to find out the optimal candidate points that cover demand points. The greedy heuristic algorithm is used to work out the solution. It is found that the optimal way of placing charging piles is to keep six existing ones and add five new ones, which can cover all demand points without overlap or inadequacy.

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