Article

Location and Expansion of Electric Bus Charging Stations Based on Gridded Affinity Propagation Clustering and a Sequential Expansion Rule

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Abstract: With the escalating contradiction between the growing demand for electric buses and limited supporting resources of cities to deploy electric charging infrastructure, it is a great challenge for decision-makers to synthetically plan the location and decide on the expansion sequence of electric charging stations. In light of the location decisions of electric charging stations having long-term impacts on the deployment of electric buses and the layout of city traffic networks, a comprehensive framework for planning the locations and deciding on the expansion of electric bus charging stations should be developed simultaneously. In practice, construction or renovation of a new charging station is limited by various factors, such as land resources, capital investment, and power grid load. Thus, it is necessary to develop an evaluation structure that combines these factors to provide integrated decision support for the location of bus charging stations. Under this background, this paper develops a gridded affinity propagation (AP) clustering algorithm that combines the superiorities of the AP clustering algorithm and the map gridding rule to find the optimal candidate locations for electric bus charging stations by considering multiple impacting factors such as land cost, traffic conditions, and so on. Based on the location results of the candidate stations, the expansion sequence of these candidate stations is proposed. In particular, a sequential expansion rule for planning the charging stations is proposed that considers the development trends of the charging demand. To verify the performance of the gridded AP clustering and the effectiveness of the proposed sequential expansion rule, an empirical investigation of Guiyang City, the capital of Guizhou province in China, is conducted. The results of the empirical investigation demonstrate that the proposed framework that helps find optimal locations for electric bus charging stations and the expansion sequence of these locations are decided with less capital investment pressure. This research shows that the combination of gridded AP clustering and the proposed sequential expansion rule can systematically solve the problem of finding the optimal locations and deciding on the best expansion sequence for electric bus charging stations, which denotes that the proposed structure is pretty pragmatic and would benefit the government for long-term investment in electric bus station deployment.

Keywords: charging stations; AP clustering; charging demand; sequential expansion

1. Introduction

According to the report "International Energy Outlook 2019" released by the U.S. Energy Information Administration (EIA) [1], the consumption of global energy is expected to increase by 50% from 2018 to 2050. With the fast growth of energy consumption, the emission of carbon dioxide would witness a significant increase. Based on the prediction of the EIA [1], emissions of carbon dioxide would rise from 28.1 billion tons in 2005 to

42.3 billion tons in 2030. Initiatives for traffic pollution emissions reduction and the commitments associated with the Kyoto Protocol require policymakers to formulate more effective and positive policies in reducing the emissions of carbon dioxide [2,3]. At present, energy consumption in urban areas accounts for 60–80% of the total amount [4]. Correspondingly, the emissions of greenhouse gas account for 70% of total emissions [4]. The World Cities Report (2016) [5,6] pointed out that about 95% of people would move to urban areas for economic reasons. Moreover, the urban population of developing countries is expected to be doubled by 2030. With the explosion of urban population, the contradiction between the energy requirements of transportation and the carrying capacity of the city would become sharper than ever. To achieve long-term sustainable development, it is necessary to implement alternative technologies and resources to replace oil-dependent mobility for public transit services in urban areas [7]. Urban buses with electric traction provide the best potential replacement option and electric charging systems are promising facilities and infrastructures for post-fossil fuel flowability [8], with which traditional traffic systems can move from non-ecological mobility towards ecological mobility [9].

Electric buses have been verified to reduce energy dependence on fossil fuels [10,11], which can substantially reduce greenhouse gas emissions. It is a crucial public requirement to build clean urban transport, and a scientifically planned electric bus system would lay the foundations for future urban city development [12,13]. Therefore, more and more cities and districts plan to promote electrically powered vehicles in the public transportation system. According to the report by the Ministry of Transport of China, the number of electric bus owners reached 400,000 by 2020. Moreover, as the Chinese central government has realized the potential significance of the preservation of the environment, large-scale implementations of electric bus programs are thus encouraged and welcomed by a growing number of local cities.

Besides air pollution, fast urbanization causes many other social problems, such as traffic congestion, urban noise, public traffic space scarcity, and so on. Considering the limitation and scarcity of urban traffic spaces, inappropriate locations and decisions regarding the size of electric bus charging stations would cause negative effects on the further development of electric-based public transit services. Moreover, a poor layout of urban traffic networks leads to network loss and the degradation of voltage profiles at some nodes [14]. For the aforementioned reasons, reasonable planning of electric bus charging stations is becoming a vital problem in supporting the sustainable development of cities. In recent years, with the fast adoption of electric buses in public transit systems, the sustainable construction and renovation of the charging stations is extremely important for green development.

In academics, many scholars have focused on the problem of the location of electric bus charging stations. To the best of our knowledge, the research subjects on electric bus charging stations can be divided into the following two categories. The first one mainly focuses on locating charging stations in future sustainable and green cities in the most economical way [15]. By reviewing the literature, different charging station location problems are proposed and analyzed within different contexts. Correspondingly, various methods are developed and applied to solve these location models under certain specific conditions.

On the charging station location problem, a large number of studies concentrate on electric vehicles rather than on electric buses. For example, Bai et al. [16] developed a cell-based model to determined locations, capacity options, and service types for electric vehicle charging stations. You et al. [17] presented a mixed-integer programming model to deal with the location of charging stations for electric vehicles under budget restrictions to maximize the population coverage. Zhang et al. [18] and Wang et al. [19] used intelligent optimization algorithms to site and determine the size of charging stations. Bouguerra et al. [20] aimed to optimize the location of charging stations through five integer linear programs based on weighted set covering models, and the model was applied in Tunis City, Tunisia. Kavianipour et al. [21] presented a methodological framework to determine the optimal locations of charging stations to build a network of charging stations,

and considered queuing delays and the feasibility of electric vehicle trips. Zhang et al. [22] focused on establishing an electric vehicle charging station site selection model under the risk of service capacity and user anxiety.

To the best of our knowledge, only a few researchers have focused on the charging station location problem in terms of the various electric bus requirements. An Kun [23] developed a stochastic integer programming model and aimed to optimize charging station locations and electric bus fleet size considering time-of-use electricity tariffs. Jing et al. [24] proposed a mixed-integer programming model to find optimal charging station locations and the swapping demand assignment of electric buses. Wang et al. [25] also presented a mixed-integer programming model to optimize charging station locations and capacities of electric buses. Different from the previous research, Wang et al. [25] put more emphases on the recharging schedules. Xylia et al. [26] introduced a mixed-integer model for optimizing the distribution of charging infrastructure for electric buses in the urban context. To ensure the best connectivity of the road network, Uslu et al. [27] proposed a mixed-integer–linear mathematical model to deal with the problem of charging station location and capacity decisions of electric buses.

The second category discusses the expansion of charging stations to enhance the investment effectiveness. As a large number of charging stations are located in the central area of the urban grid load, the surge in charging load will affect the operation and planning of the urban grid [28]. In general, the construction or expansion of new charging stations is restricted by various conditions, such as the size for land use, the scale of capital investment, and the power grid load. Therefore, based on the aforementioned conditions, several researchers constructed models to investigate the expansion of electric vehicle charging stations. For example, Xiang et al. [29] set up a multi-objective planning framework for the expansion of electric vehicle charging stations. This framework achieves the minimization of economic costs, the maximization of the utilization rate of the charging stations, and the maximization of the reliability level simultaneously. Kabli et al. [30] developed a two-stage stochastic programming model that can be applied to determine a power grid expansion plan for positioning electric vehicle charging stations. Meng et al. [31] proposed an optimization model for siting and sizing charging stations for electric taxis. Wang et al. [32] led a different study by considering the expansion of electric bus charging stations and presented a scheduling-based charging station expansion strategy for electric buses to validate the effectiveness and efficiency of the charging station expansion process.

After reviewing the two research categories, an algorithm called AP clustering was seen to have been introduced to solve the facility location problem. AP clustering has already been tested as a simple clustering algorithm based on the propagation of neighbor information [33], and has widely been applied to several fields, including energy efficiency analysis [34], image processing [35], text clustering [36], smart grid systems [37], wireless sensor networks [38], location problems [39,40], and so on. By sharing the experience of AP clustering in other studies, this paper analyzes the location problem of electric bus charging stations.

In the general setting, AP clustering assumes that all vehicle (electric buses in this paper) charging stations have the same probability of being selected as the clustering point. However, the impacts of some objective factors, for example, the degree of transportation convenience and layout of the existing stations, must necessarily be considered when planning the location of the charging station. Furthermore, considering the gridding method can significantly decrease the computational complexity [41], this paper introduces the gridding method by assigning points to a candidate on a grid of whole districts. After the candidate locations are ascertained, the expansion plan is presented to decide which charging station should be expanded first, and which would be interfered by factors such as the operating cost, charging facility investment cost, and so on. Thus, by analyzing the weights of the impacting factors on each candidate station, a comprehensive evaluation based on the total score of all weights is performed, which indicates whether a candidate location should be expanded as the charging station.

Considering the aforementioned studies, the expansion work either puts emphasis on developing the analytical method, or concentrates on formulating the comprehensive evaluation models. In view of the above findings, different from the algorithm development studies, the main work of this paper is to develop a systematic framework that can find the most proper locations and the expansion sequence of bus charging stations simultaneously. Specifically, firstly, this study combines the superiorities of the AP clustering algorithm and the gridding method to find the optimal candidate stations for electric bus charging stations. Secondly, considering the fast growth of charging demand, this study proposes a sequential expansion rule for optimizing the expansion of charging stations through an empirical investigation in Guiyang city, China. The main contribution of the paper is mainly reflected in following three aspects:

(a) For the first time, this study combines the superiorities of AP clustering and the gridding method to find the best locations of electric bus charging stations by considering multiple factors, e.g., the power consumption cost, the innovation cost, and the traffic demand, which provides new considerations in the field of electric bus charging stations.

(b) To alleviate to investment pressure for the government and meet the charging demand with different priorities, a sequential expansion rule was constructed to find the optimal locations of the new charging stations under the expansion of the buses by considering four kinds of factors, i.e., the investment cost of charging facilities, the operating cost of charging stations, additional costs, and the revenue of energy charging system.

(c) An empirical investigation in Guiyang city, China, was performed. The results of the empirical research show that the optimized locations for electric bus charging stations under bus expansion would contribute to the entire electric bus system network.

The remainder of this paper is organized as follows. Section 2 introduces the superiorities of the AP clustering algorithm and the gridding method. Section 3 discusses the implementation of the AP clustering algorithm based on the gridding method in the case of Guiyang city. An optimization model for the location of the electric bus charging stations and the expansion sequence of bus charging stations are presented and an empirical investigation of Guiyang is carried out to discuss the implementation effectiveness of the proposed model in Section 4. Section 5 concludes the paper with a summary of the findings and limitations of the research as well as the directions for future research.

2. Gridded AP Clustering for Location Planning

As the most important facility for electric bus operations, electric charging stations are the most critical resource for the whole charging network operation. However, the service capabilities of the whole charging network would be seriously affected by the distribution of the charging stations. Correspondingly, a good layout of the electric charging stations would create benefit for city transportation development in two aspects. The first one lies in that the investment cost in construction can largely be saved by rationally planning the number of charging stations. The other one reflects that it can help strengthen the service ability in terms of the requirements for improving the service efficiency of the charging piles, the stableness of the charging grid, and the degree of dispersion of charging demands. Therefore, properly planning the charging stations is an interesting research area that absorbs many scholars devoted to developing numerous studies in this area. In this section, AP clustering is presented preliminarily. Then, improved AP clustering with the gridding rule, called gridded AP clustering, is proposed to overcome the slow search speed of AP clustering and realize multi-criteria decision.

2.1. AP Clustering

Clustering is welcomed by many scholars to find candidate locations to meet the service requirements. For example, Pang et al. [42] tried to find the optimal location for logistics centers by using fuzzy c-means clustering. Gao et al. [43] applied K-means clustering to find the best location for vehicle visiting depots. Of all the clustering methods,

AP clustering has the advantage of ease of understanding and use, and is applied in this paper to investigate the location problem of electric bus charging stations.

AP clustering was proposed by Frey and Dueck [44] based on the "message-passing" between data points. In AP clustering, all data points are considered as potential clustered/center points. If a data point is selected as the center point, it is called the "exemplar." To begin with, AP clustering randomly selects a data point as the exemplar and iteratively refines it via a message-passing procedure. Therefore, the main characteristic of AP clustering compared to K-means clustering is that the number of clustering centers does not need to be specified in advance, which denotes that AP clustering can help find the optimal number of locations in more general situations.

Specifically, the principle of AP clustering is based on measuring the similarity between paired data points. For data points i and k, the similarity $S(i,k)$ denotes the degree of fitness of data point i to data point k if k is appointed as the exemplar. In general, the similarity $S(i,k)$ is defined as a negative squared error and calculated based on Equation (1).

$$S(i,k) = -\left|(x_i - x_k)^2 + (y_i - y_k)^2\right|, \ i \neq k \tag{1}$$

If $i = k$, AP clustering is taken as a real number $S(k,k)$ for each data point k. The highest data point k is called the "preference," and it denotes that data point k gets a higher probability as the exemplar. Furthermore, the number of exemplars is affected by the input preferences. In other words, those data points with higher preferences will have more possibilities of being chosen as exemplars.

After the similarity has been calculated, two kinds of messages, "responsibility" and "availability," are exchanged to iteratively refine the exemplars to obtain a lower squared error. The responsibility $r(i,k)$ is sent from data point i to candidate exemplar k, which reports to what extent data point k is suited to be the exemplar for data point i considering other candidate exemplars for data point i simultaneously. The responsibilities are given as:

$$r(i,k) = s(i,k) - max\{a(i,k') + s(i,k')\} \quad s.t. \quad k' \in \{1, 2, \cdots, N\}, k' \neq k \tag{2}$$

For $i = k$, $r(k,k)$ is called the "self-responsibility," which denotes that k is an exemplar $S(k,k)$ by testing whether point k is suitable to be assigned to other exemplars. In other words, point k is better taken as an exemplar than assigned to other exemplars when $r(k,k)$ is positive. In addition, the availability $a(i,k')$ is set to zero before the iteration.

The availability $a(i,k)$ is sent from candidate exemplar k to data point i. It reflects the information for the degree of availability of candidate exemplar k to be chosen as the exemplar of data point i compared to the other data points choosing data point k as the exemplar. The availability $a(i,k)$ is calculated as follows:

$$a(i,k) = min\left\{0, r(k,k) + \sum_{s.t. \ i' \notin \{i,k\}} max\{0, r(i',k)\}\right\} \tag{3}$$

It should be pointed out that $a(k,k)$ is the "self-availability," which is given as:

$$a(k,k) = \sum_{i' \neq k} max\{0, r(i',k)\} \tag{4}$$

To avoid numerical oscillations for responsibility and availability, a damping factor λ is introduced with a range between 0 and 1. Then, the responsibility and availability are updated by Equations (5) and (6), respectively.

$$r(i,j) = \lambda r(i,j) + (1 - \lambda)(s(i,j) - max\{a(i,k) + s(i,k)\}) \tag{5}$$

$$\begin{cases} a(i,j) = \lambda a(i,j) + (1-\lambda) min\left\{0, r(j,j) + \sum_{k}\{max(0, r(k,j))\}\right\}, i \neq k \\ a(i,i) = \lambda a(i,i) + (1-\lambda)\sum_{k}\{max(0, r(k,j))\}, j \neq k, j \neq i \end{cases} \tag{6}$$

The iteration processes of AP clustering are given as follows:

Step 1: Initialization and parameter setting. Set the maximum iteration as max-gen, the stagnation step for iteration in finding exemplar as stableNum, and the damping factor λ as 0.7.

Step 2: The similarity $S(i,k)$ calculation. The similarity of each data point is calculated by Equation (1), the availability $a(i,k')$ is set as zero, and the preference $S(k,k)$ is preset as the median of the similarity.

Step 3: The responsibility $r(i,k)$ and self-responsibility $r(k,k)$ are computed based on Equation (2).

Step 4: The availability $a(i,k)$ and self-availability $a(k,k)$ are calculated based on Equations (3) and (4), respectively.

Step 5: The responsibilities $r(i,k)$ and the availability $a(i,k)$ are updated based on Equations (5) and (6), respectively.

Step 6: Searching repetition. Steps 3 to 5 are repeated until the maximum iteration is reached or stableNum is satisfied, where stableNum is a preset number to stop the searching process if the results are unchanged with the stableNum steps.

Traditional AP clustering has been shown to be an effective clustering method [45], though there are two shortcomings for AP clustering. Firstly, the convergence speed of AP clustering is slow, especially for large point cases, which results in the optimal solution not being found efficiently. This reflects the weaknesses of traditional AP clustering in search speed and performance. Secondly, for traditional AP clustering, all candidate data points have the same probability of being selected as the exemplars. In fact, exemplar selection is not only related to relative positions of the paired data points, but the objective impacting factors also play important roles in the exemplar decision. For example, factors such as the traffic convenience, power facility renovation cost, station scale, etc., are influential and may impact the final results. In other words, the data points being selected as the exemplars with different probabilities would depend on the impacting factors. Therefore, this paper seeks to make improvements to overcome the two obstacles in applying traditional AP clustering to find the optimal locations of electric bus charging stations.

2.2. Gridded AP Clustering

To overcome the aforementioned two weaknesses of traditional AP clustering, map gridding is introduced. Then, a multi-criteria evaluation framework that can synthetically assess the objective factors of the electric bus charging station candidates is proposed. Finally, gridded AP clustering for finding the optimal locations of the electric bus charging stations is formulated.

By analyzing the preliminary AP clustering, we can see that the algorithm complexity of AP clustering [46] is $O(N * N * LogN)$ (N is the number of data points), whereas the algorithm complexity of K-Means is only $O(N * K)$. It should be noted that there are hundreds or even thousands of candidate bus stations in a city, which is a great challenge for applying AP clustering considering the unimaginable algorithmic complexity that AP clustering faces. Thus, to accelerate the iteration of AP clustering, a two-dimensional map is divided into grids of equal size and the candidate points are grouped and uniformly distributed on the grids.

For another challenge of AP clustering, i.e., how to evaluate the preferences of each candidate point, a synthetic evaluation framework is introduced. Based on the aforementioned situation, planning the location of an electric bus charging station is closely interfered with by multiple conditions of candidate points. In general, the decision-maker usually evaluates from two aspects [47] to decide whether a candidate station is suitable to be a charging station.

On one hand, the construction cost of candidate charging stations is considered, which includes the land cost and the cost of power facility renovation. On the other hand, decision-makers need to evaluate whether the objective conditions, such as the load capacity of the power network, the traffic, the number of buses at the candidate station, and the charging demand of the candidate station, meet the requirements for positioning the charging stations [47]. In this paper, six crucial impacting factors are chosen to reflect the decision-makers' objectives on these candidate points.

In this paper, the expansion of charging stations is considered to meet the continuous growth of electricity charging demand. Specifically, with the growth of charging demand, it is necessary to supplement the charging infrastructure and enhance the load of the electricity grid, which would involve renovation costs. Moreover, parking lot expansion would be considered with the growth of bus charging demand, which would involve land expansion costs. Based on the experience in the Guiyang case, the candidate charging stations have already been found to be equipped with basic electric facilities for lights and located near residential communities or workplaces. Thus, if a candidate station is chosen to be renovated, the infrastructure costs and power facility updating costs for renovation need to be considered.

In general, the charging capacity of an electric bus charging station is directly affected by the load capacity of the power grid. Thus, the output power is selected to measure the power system status of each candidate station. In practice, the candidate station with the largest load capacity of the power grid is more suitable to be set as the charging station. Therefore, the weight of the service status of the power system is given as:

$$\theta_i^{power} = \mu_{power}\left(P_i/\overline{P}\right) \tag{7}$$

where P_i is the output power of candidate station i, and $\overline{P}$ is the average output power of all candidates. μ_{power} is an experience coefficient to adjust the importance of factors. Specifically, if the decision-maker believes that the status of the power system plays a more important role than the other factors in ascertaining the location of an electric bus charging station, a higher value would be given to the weight of that factor.

Furthermore, the facility renovation cost is a necessary consideration in planning an electric bus charging station location. Thus, the weight of the cost for power facility renovation is given as:

$$\theta_i^{cost} = \mu_{cost}\left(\overline{C}/C_i\right) \tag{8}$$

where C_i is the power facility renovation cost of candidate station i, $\overline{C}$ is the average power facility renovation cost of all candidates, and μ_{cost} is an experience coefficient.

Similar to the aforementioned factors, the weights of the public factors are given as Equations (9)–(12).

$$\theta_i^{scale} = \mu_{scale}\left(S_i/\overline{S}\right) \tag{9}$$

$$\theta_i^{land} = \mu_{land}\left(\overline{C}^{land}/C_i^{land}\right) \tag{10}$$

$$\theta_i^{demand} = \mu_{demand}\left(D_i/\overline{D}\right) \tag{11}$$

$$\theta_i^{traffic} = \mu_{traffic}\left(T_i/\overline{T}\right) \tag{12}$$

where μ_{scale}, μ_{price}, μ_{demand}, and $\mu_{traffic}$ are the experience coefficients. S_i denotes the service scale of the candidate bus station i and $\overline{S}$ is the average scale of all candidate bus stations. C_i^{land} is the land cost of candidate station i and $\overline{C}^{land}$ is the average land cost of all candidates. D_i is the charging demand of candidate station i and $\overline{D}$ is the average charging demand of all candidate stations. It should be noted that the traffic condition of the candidate station is assumed to be the width of the road. Therefore, T_i is the width of the road for candidate station i and $\overline{T}$ is the average width of the road. After the objective factors and the weight of each candidate station have been obtained, the results are then taken as the input data of AP clustering.

Based on the procedure for the synthetic evaluation process, the weight of each candidate station chosen as an exemplar is obtained. The steps of the gridded AP clustering are given as follows:

Step 1: Initialization and parameter setting. Parameters such as the maximum iteration, the amount of iteration stagnation, and the damping factor λ are set as max-gen as stableNum and 0.7, respectively.

Step 2: Map gridding and weight calculation. The map is divided into grids of the same size. The weights of each grid are calculated based on Equations (7)–(12).

Step 3: Similarity $S(i,k)$ computation. For each data point, the similarity is calculated by Equation (1) and the availability $a(i,k')$ is initialized as zeros. The preference $S(k,k)$ is calculated as follows:

$$S(k,k) = \theta_k^{power}\theta_k^{cost}\theta_k^{scale}\theta_k^{land}\theta_k^{demand}\theta_k^{traffic} / P_{rec} \tag{13}$$

where P_{rec} is an adjustment coefficient that controls the strictness of the location planning of a charging station. Specifically, the larger P_{rec} is, the stricter the conditions for ascertaining the charging stations are, so a smaller number of charging stations is selected.

Step 4: The responsibility $r(i,k)$ and self-responsibility $r(k,k)$ are calculated based on Equation (2).

Step 5: The availability $a(i,k)$ and self-availability $a(k,k)$ are calculated based on Equations (3) and (4), respectively.

Step 6: The responsibility $r(i,k)$ and the availability $a(i,k)$ are updated by Equations (5) and (6), respectively.

Step 7: Algorithm repetition. Steps 4 to 6 are repeated until max-gen is reached or stableNum is satisfied. The clustered results of the locations of charging stations are the output.
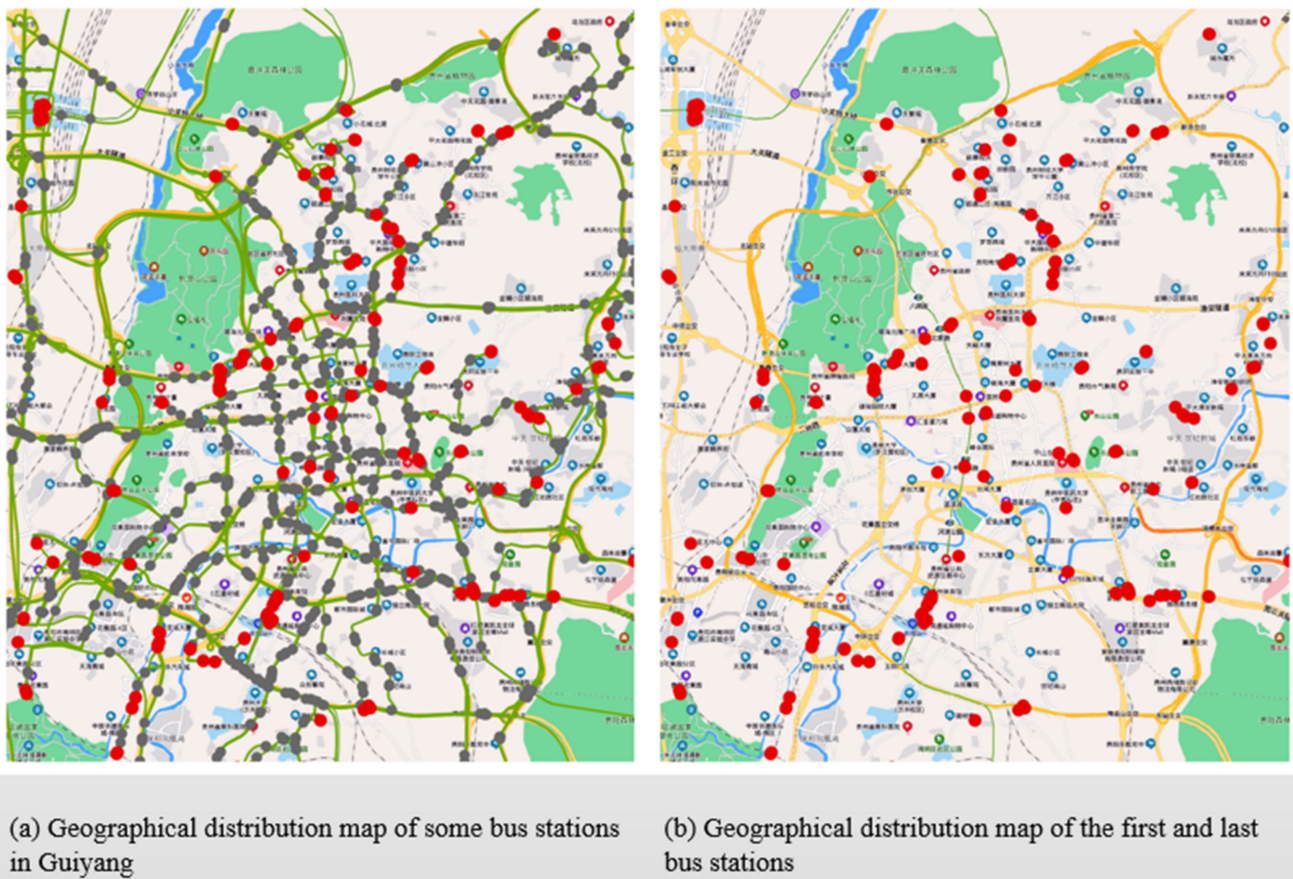
3. The Case of Guiyang City

Guiyang city, the capital of Guizhou Province, is located in the southwest of China, with a resident population close to 4,971,400. With the central government's encouragements of ideas for sustainable and green development, the western districts of China have put much emphasis on natural resource protection and fragile environment preservation. Guiyang is the most typical city in practicing eco-friendly development strategies. Furthermore, Guiyang is in the second batch of New Energy Vehicle Promotion and Application Demonstration Cities in China. It is obvious that Guiyang city has a large demand for public transportation renovation. Therefore, combined with national policies and the actual needs in Guiyang, the development of electric buses is important for promoting new energy vehicle implementations. The electric bus station location plan of Guiyang was selected to verify the effectiveness of the proposed gridded AP clustering. Because Guiyang is a mountain city, the terrain of which is covered by mountains and hills, with a mountain area of 4218 square kilometers, it faces the problem of fewer land resources for the location and expansion of electric bus charging stations. Therefore, the location problem of electric bus charging stations becomes a key challenge for the decision-makers of Guiyang.

3.1. Data Preprocessing

This study used Python 3.8 to obtain the geographic location information of 269 bus lines in the main urban area of Guiyang through Baidu® Map. The distribution of the stations is shown in Figure 1a. The gray dots represent all the intermediate stops of the bus lines and the red dots represent the first and last stops of the bus lines. The focus of this paper is on the geographic location information of all the first and last bus stops. Figure 1a was reprocessed to obtain a filtered map of the geographic locations containing the first and last bus stops of all bus lines; the filtered results are illustrated in Figure 1b with a total number of 121 red dots.

(a) Geographical distribution map of some bus stations in Guiyang

(b) Geographical distribution map of the first and last bus stations

Figure 1. The geographical distribution map of some bus stations in Guiyang.

Based on the filtered map, the gridding rule was introduced to block the bus stops. In particular, the geographic distribution map containing the first and last bus stops was equally divided into small zones through the gridding rule. Consequently, all the uniformly scattered bus stops were assigned to the gridded zones, which were assumed to be the gridding blocks with the location information pertinent to each stop (candidate charging station). Thus, each gridded zone (represented by the data point (i, j)) covers a certain number of bus stops. Moreover, it should be noted that the gridded zone provides a feasible area for positioning the bus charging station but is not a fixed specific location, which gives the necessary flexibility for decision-makers.

This paper divided the map into grids, and the length of each grid is one kilometer. A gridded map containing the geographic distribution of the first and last bus stops was thus obtained (see Figure 2). The light gray lines divide the map into blocks, which are represented as the grids. In different gridded areas, the average land cost, charging demand, power supply network charge load, power facility renovation cost, and construction scale are different, which would have integrated impacts on the electric bus charging location selection and expansion planning.

In gridded AP clustering, the magnitude of the grid weight is critical for determining the location of the charging station. If the comprehensive weight of a grid is larger, it means that the grid area is more likely to be chosen as the location for the charging station. In Guiyang's case, six factors affecting the grid weight were considered (see Table 1).

The calculation process was as follows: Firstly, the similarity matrix was constructed by Equation (1). Then, P_{rec} in Equation (13) was updated. Thirdly, the responsibility and credibility of each candidate area to the cluster center was sequentially calculated by Equations (2)–(4). Finally, the clustering results were output through the evaluation. It should be noted that the value of P_{rec} is usually assumed to range from 1 to 10. For the case

of Guiyang, 3, 7, and 10 were given to P_{rec} for illustration. Correspondingly, three gridded AP clustering analyses were performed independently, and the number of cluster centers under the three P_{rec}s were computed as 14, 11, and 9, respectively.
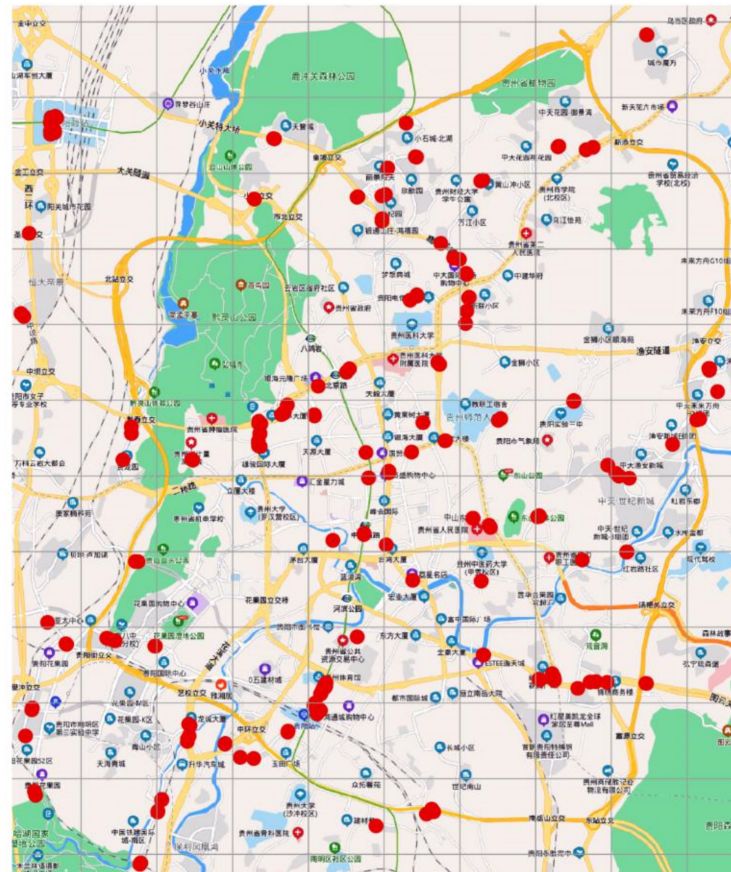

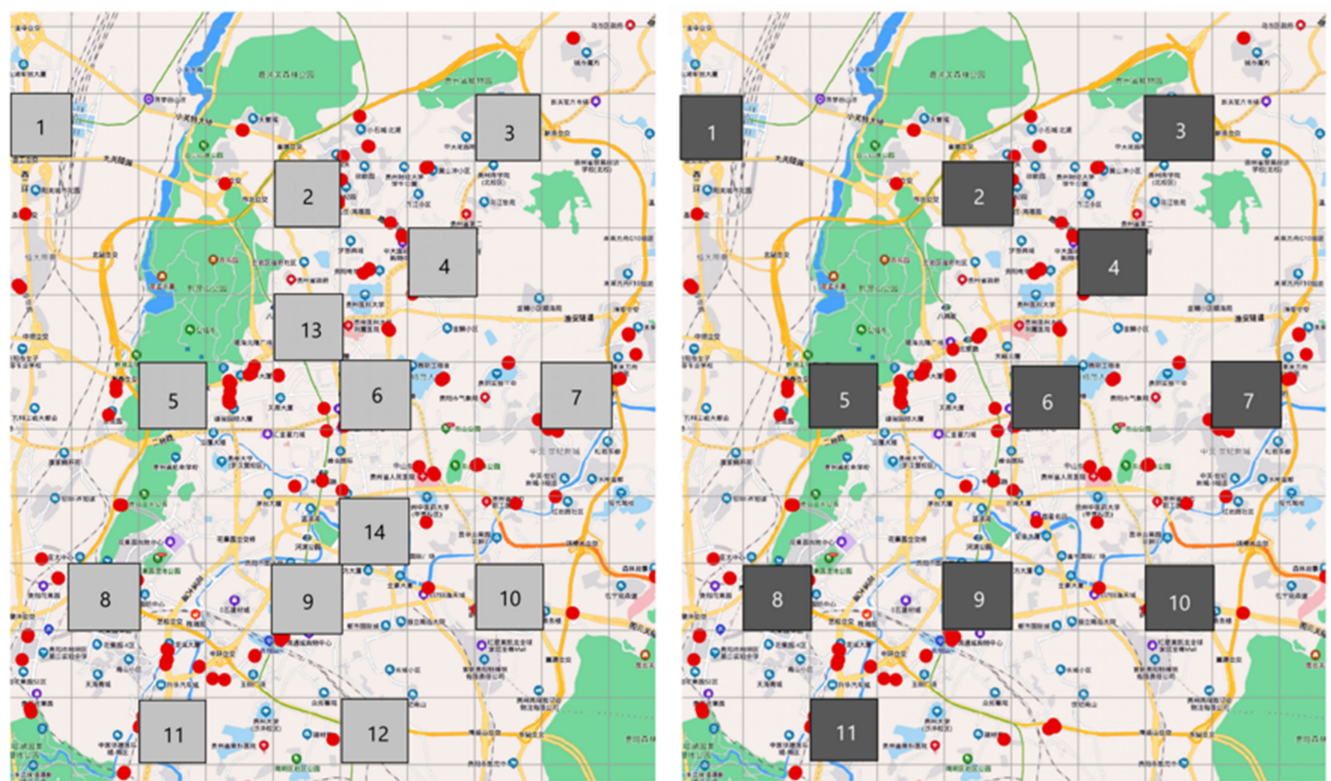**Figure 2.** Geographic distribution grid map.

Table 1. Notation descriptions.

No.	Factors	Notations
1	The impact condition of the power system	θ_i^{power}
2	The cost of power facility renovation	θ_i^{cost}
3	The number of buses in the candidate station	θ_i^{scale}
4	Land cost	θ_i^{land}
5	Charging demand	θ_i^{demand}
6	Traffic conditions	$\theta_i^{traffic}$

3.2. Calculation Results under the Three P_{rec}s

(1) The geographical distribution of stations was obtained when P_{rec} was set to 3 (see Figure 3a). Each light gray grid represents a candidate charging station positioning area. In total, there were 14 candidate areas from left to right and from bottom to top. The 14 candidate points are labeled sequentially.

(2) The geographical distribution of stations was obtained as shown in Figure 3b when P_{rec} was set to 7. Similarly, each gray-black gridded block represents a candidate charging station. In Figure 3b, there were 11 candidate points, which are labeled with sequential numbers.

(a) Prec=3 geographic distribution map of candidate points   (b) Prec=7 geographic distribution map of candidate points

Figure 3. Geographical distribution of candidate stations.

From the computational results of the gridded AP clustering, the number of clustered centers (stations), geographic location coordinates, and the number of bus stations responsible for the area were obtained. The coordinate origin was set as the grid point in the lower left corner of the geographic distribution map. Each grid interval represented the unit coordinate interval 1. For example, the coordinates of label 1 were (1, 9). Similarly, the geographic coordinates of the other public transportation candidate points are shown in Table 2 for P_{rec} = 3. The results of the labeled candidate points in Tables 2 and 3 are illustrated in Figure 3a and b, respectively.

Comparing the results in Tables 2 and 3, it can be seen that different $P_{rec}s$ corresponded to different numbers of bus charging stations. Specifically, when P_{rec} = 3, the number of candidates charging stations was 14, and when P_{rec} = 7, the number of candidates charging stations was 11. As the value of P_{rec} increased, the comprehensive weight of all the impacting factors of the candidate stations became larger. This means that it had a larger possibility of being the candidate point or bus stop selected as the charging station. In contrast, the grid points with poor evaluation results based on those impacting factors had small opportunities of being selected as candidate stations. Therefore, the larger P_{rec} is, the fewer candidate charging stations are obtained.

Furthermore, it was found that all the candidate charging stations in Table 3 were included in Table 2, whereas candidate stations 12, 13, and 14 in Table 2 were not discarded in Table 3. Point No. 13 was not selected as a candidate because the traffic convenience of No. 6 was better than that of candidate No. 13. Thus, the priority of candidate No. 13 being selected as a candidate charging station was small. Similarly, the priorities of points 12 and 14 being selected as candidate stations were lower than those of the surrounding counterparts of points 12 and 14. The reason can be seen in Figure 3 that there are no other bus lines in the surrounding areas.

Table 2. Clustered information when P_{rec} = 3.

Station No.	Coordinate	Number of Bus Stops	Station No.	Coordinate	Number of Bus Stops
1	(1,9)	7	8	(1,2)	9
2	(4,8)	10	9	(4,2)	9
3	(7,9)	4	10	(7,2)	11
4	(6,7)	7	11	(2,0)	11
5	(2,5)	8	12	(5,0)	4
6	(5,5)	8	13	(4,6)	12
7	(8,5)	11	14	(5,3)	10

Table 3. Clustered information when P_{rec} = 7.

Station No.	Coordinate	Number of Bus Stops	Station No.	Coordinate	Number of Bus Stops
1	(1,9)	7	7	(8,5)	11
2	(4,8)	10	8	(1,2)	9
3	(7,9)	4	9	(4,2)	17
4	(6,7)	12	10	(7,2)	13
5	(2,5)	11	11	(2,0)	11
6	(5,5)	16	-	-	-

(3) The geographical distribution of candidate points was obtained as shown in Figure 4 when P_{rec} = 10. Each black grid represents a charging station. At this time, the number of stations was reduced to 9. The clustering information is shown in Table 4.
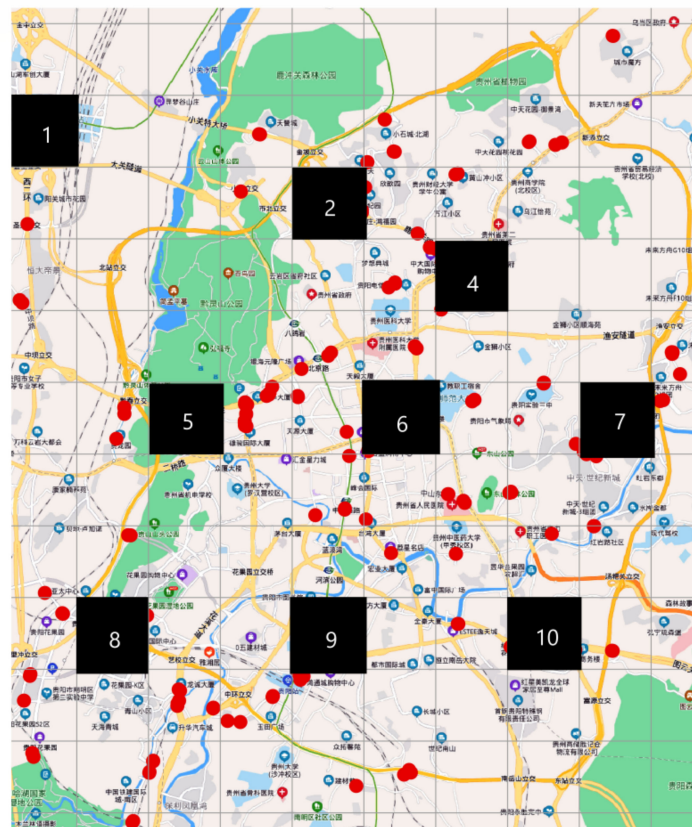

Figure 4. P_{rec} = 10 geographical distribution map of candidate points.

Comparing the results in Table 4 with those in Tables 2 and 3, it can be seen that 9 candidate charging stations in Table 4 were all included in Tables 2 and 3. This explains that the candidate stations in Table 4 had the highest priority, and these candidate stations should be constructed first.

Table 4. Clustered information when P_{rec} = 10.

Station No.	Coordinate	Number of Bus Stops
1	(1,9)	7
2	(4,8)	14
4	(6,7)	12
5	(2,5)	11
6	(5,5)	16
7	(8,5)	11
8	(1,2)	16
9	(4,2)	21
10	(7,2)	13

4. Sequential Expansion Model

In recent years, the rapid increase in electric buses in cities has caused great charging pressure on existing electric bus charging station networks. However, the construction of new electric bus charging stations will involve large-scale investment costs for cities. Network expansion of existing electric bus charging stations is the most economical way to support sustainable development for long-term planning of the public transit of a city. In addition, most electric bus charging stations are located in central areas of cities and the surging charge demand poses a challenge to the current power grid supply. Therefore, the deployment of the energy service (storage planning, charging, and maintenance) system is a necessary measure to reduce the impact on the power grid supply during the process of expansion.

Based on these conditions, for the expansion of electric bus charging stations, decision-makers need to formulate a well-designed expansion plan with the lowest total long-term cost. In particular, decision-makers need to determine which charging stations should be expanded first and how many charging facilities should be planned, and invest in those charging stations. Thus, in this section, a sequential expansion rule with the lowest total cost as the objective function for constructing electric bus charging stations is presented.

4.1. Sequential Expansion Rule

The assumptions to develop the expansion rule are given as follows:

(1) All electric bus lines are closed loop lines. In other words, the first and/or last stops are the parking lots for electric buses.
(2) The energy charging system is introduced to reduce the impacts on the power system.
(3) The locations obtained by gridded AP clustering are the candidate locations for charging stations.

Based on the assumptions, the total cost is tallied based on four parts, i.e., the investment cost of charging facilities C_1, the operating cost of the charging station C_2, additional costs C_3, and the revenue of the energy charging system C_4.

The investment cost of charging facilities C_1 is given as:

$$C_1 = \sum_{i=1}^{N} \left[(W_c + h_1 + a_1 b_i) \frac{r_0(1+r_0)^{y_c}}{(1+r_0)^{y_c} - 1} + C_i^D D_i \right] \tag{14}$$

where N is the total number of electric bus charging stations in existence, W_c is a given fixed investment cost of expanding a single charging station, h_1 is the cost of deploying the energy charging system, a_1 is the price of the charging facility, b_i is the number of added charging facilities in charging station i, r_0 is the discount rate—which was considered by

Xylia et al. [26] to reflect the asset depreciation—y_c is the operating life, C_i^D is the land price of charging station i, and D_i is the area occupied by charging station i.

The operating cost of charging station C_2 is given as:

$$C_2 = \sum_{i=1}^{N} \varepsilon[a_1 b_i + E_i] \tag{15}$$

where C_i^D is the land price of charging station i, D_i is the area occupied by the charging station i, E_i is the basic cost for charging station operation, and ε is the convert coefficient.

Additional costs C_3 refers to the spent cost of an electric bus when passing between the parking lot and charging station. It is given as:

$$C_3 = P \times C_e \times \sum_{k=1}\sum_{i=1} (d_{ki} n_c(k) XY(k,i)) \times 365 \tag{16}$$

where P represents the power consumption of an electric bus per kilometer, C_e is the price of unit power, d_{ki} represents the distance between bus station k and charging station i, $n_c(k)$ is the charging times of bus station k, X is the expansion scheme matrix, Y is the charging scheme matrix of the added charging demand, XY is the scheme matrix composed of 0–1, and $XY(k,i) = 1$ represents that the charging station i will be expanded and the electric bus at the k-th station will be charged at the i-th charging station.

The energy charging system can share part of the electric load by discharging during peak demand periods and storing energy during low peak demand periods, which reduces the cost of energy loss and the power supply cost. Therefore, the revenue of energy charging system C_4 is given as:

$$C_4 = \omega C_2 - C_r - C_t \tag{17}$$

where ω represents the ratio of the operating cost of the energy charging system to the operating cost of the charging station, and C_τ and C_t are the energy loss cost and the power supply cost reduced by the energy charging system, respectively.

The total cost is the summation of the investment cost, operating cost, additional cost, and the revenue of the energy charging storage system, which is given as:

$$TC = C_1 + C_2 + C_3 + C_4 \tag{18}$$

In addition, four constraint sets are considered in the model. The first constraint is given as Equation (19), which is set to ensure each electric bus can be charged at only one charging station.

$$\sum_{i=1}^{N} XY(k,i) = 1 \tag{19}$$

The second constraint is the charging demand constraint. This means that the charging capacity of each charging station must meet the charging demand.

$$rb_i \geq XY(k,i)F(k,i) \quad for \quad i = 1,2,\cdots,N \tag{20}$$

where r is the maximum charging capacity of a single charging facility. $F(k.i)$ represents the added charging demand of the electric bus at k-th station, which is planned to be charged at the i-th charging station.

The third constraint is proposed to ensure that an electric bus will not be charged if a charging station is too far away.

$$XY(k,i) \cdot d_{ki} \leq L_{\max} \quad for \quad i = 1,2,\cdots,N \tag{21}$$

where $L_{\max}$ is the pre-given maximum charging service radius.

Finally, to guarantee the safety of the electric power grid system, the last constraint requires the power load of the charging facility to be less than the maximum power load of the electric system.

$$P_{\max} > \sum_{i=1}^{N} u(1 - 20\%)C_b b_i \tag{22}$$

where $P_{\max}$ is the maximum power load of the electric system, and u is the power load of a single charging facility and $1/u$ is the time for a single charging facility to fill up an electric bus, C_b is the total electric power for an electric bus, b_i is the total number of the charging facilities in charging station i. Moreover, based on experience, when the SOC (State Of Charge) of battery is less than 20%, the battery is not suitable for high current charging and discharging. In order to guarantee the battery service life, the threshold of SOC for battery is set to 20%. Therefore, $u(1 - 20\%)C_b$ represents the power load of a single charging facility per unit time, $u(1 - 20\%)C_b b_i$ is the power load per unit time of the charging station i, and $\sum_{i=1}^{N} u(1 - 20\%)C_b b_i$ represents the total power load per unit time of the entire system.

4.2. A Case Study on Guiyang

Based on the results in Tables 2–4, the charging stations were planned in three stages. In the first stage, the regional point set (1, 2, 4, 5, 6, 7, 8, 9, 10) denoted that the candidate stations should be expanded first. Then, the candidate charging stations in the point set (3, 11) followed. Finally, the candidate charging stations in set (12, 13, 14) were expanded. At the first stage, 9 candidate charging stations (P_{rec} = 10) were selected and are presented in Table 5.

Table 5. P_{rec} = 10 candidate point clustering information.

Station No.	Coordinates	Number of Bus Stops	New Order
1	(1,9)	7	1
2	(4,8)	14	2
4	(6,7)	12	3
5	(2,5)	11	4
6	(5,5)	16	5
7	(8,5)	11	6
8	(1,2)	16	7
9	(4,2)	21	8
10	(7,2)	13	9

For the convenience of description, the candidate stations in Table 5 were renumbered as 1–9 and listed in the last column of Table 5.

The parameters were provided as follows: The fixed investment of the charging station was CNY 2 million, and the price of deploying an energy system was CNY 800,000. Based on previous experience, the implementation of an energy charging system can reduce the present value of the total cost by 4.08%. The unit price for a set of charging facilities a_1 was CNY 500,000, and the base value of the number of charging facilities was set as 1. The depreciation period y_c was 15 years, and the discount r_0 was 8%. By sharing the experience from Qian et al. [48], ε was set as 15%. The electricity price per unit of electricity in the planned area was CNY 0.7124/kwh for ordinary industrial electricity in Guiyang. The electric bus was set to BYD® K8, and the electricity consumption per unit distance of BYD® K8 bus was 0.74 kWh/km [48]. The maximum distance from the demand point to the charging station was set to 15 KM.

Based on the proposed sequential expansion rule, the optimal plan for the selection of a charging station with an energy charging system was obtained as follows: If four electric bus charging stations with an energy charging system were expanded, the total social cost would be at least CNY 10.91 million/year. The specific planning scheme is shown in Table 6 as follows.

Table 6. Overall planning and deployment scheme for charging stations.

| Station No.	Coordinates	Number of Bus Stops	Number of Charging Facilities
2	(4,8)	14	21
5	(5,5)	16	29
7	(1,2)	16	29
8	(4,2)	21	35

From the results in Table 6, it can be seen that there were four selected candidate charging stations with the largest number of first and last stops in the grid. The four candidate stations had large charging requirements on the electric charging demand. The expansion of the charging station with an energy charging system could effectively alleviate the load pressure on the grid at the demand peaks and reduce the power supply costs and grid loss costs.

The comparison of the construction costs between the plans with the sequential expansion rule and without the sequential expansion rule is provided to verify the effectiveness of the proposed rule. The comparison scheme was arranged so that based on the candidate locations obtained by gridded AP clustering, all the charging stations would be expanded simultaneously, and the component costs and total cost were taken for comparison. The comparison results are presented in Table 7.

Table 7. Comparison table of the optimization scheme (Unit: CNY 10,000).

Cost	Optimization Scheme	Comparison Scheme
Investment cost of charging facilities $C1$	723.49	1286.98
Annual operating cost $C2$	72.35	198.71
Additional loss cost $C3$	351.77	0
Energy charging system revenue $C4$	−56.51	−78.78
Total social cost TC	1091.1	1406.91

To illustrate the differences of the cost components for the two optimized schemes, Figure 5 is given as follows.
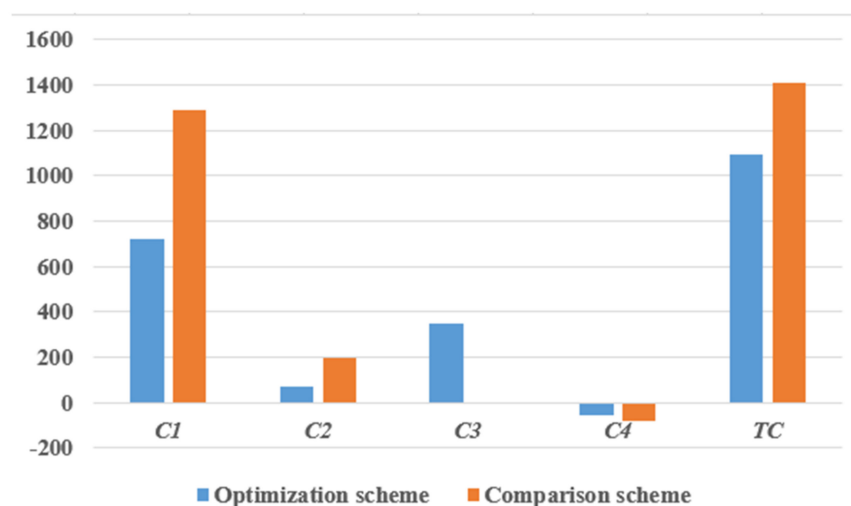
Figure 5. Comparison of optimized total social costs.

Based on the results in Table 7, it can be seen that the minimum total cost of the optimal plan is CNY 10.91 million/year under the proposed rule. For the compared plan, the total cost is CNY 14.07 million/year. This means that the proposed rule can help save CNY 3.16 million/year in public expense.

Based on the above analyses, two points of the management insights were obtained. (1) It is necessary match the construction/expansion pace of electric charging stations with the demand expansion and capital investment efficiency. Thus, comprehensive benefits can be obtained by performing the multiple-stage deployment plan for electric buses by considering different social factors. (2) The focuses on panning electric charging stations change with the evolution of the promotion of the project. In the initial stages, it is better for the decision-makers to put the emphasis on planning a reasonable number of charging facilities to control investment costs. For the remaining stages, decision-makers should make the effort to reduce the operating costs of the charging stations to achieve long-term benefits.

5. Conclusions

In response to problems such as public green transit demand increasing and the effective deployment of public electric charging stations, this paper investigated the electric bus station location problem. In particular, traditional AP clustering was improved upon to sequentially plan the charging station locations of electric buses by gridding the map of an area. Then, the optimal locations of the energy charging system were planned based on the charging station location results obtained. An empirical investigation of Guiyang was performed to verify the effectiveness of the gridded AP clustering algorithm. The results of the empirical investigation show that the proposed sequential expansion rule can reduce the total construction cost effectively by meeting the charging demand and optimizing the construction stages of the electric bus charging station network.

This paper tried to develop a feasible evaluation framework for systematically location charging station candidates and sequential construction of these stations. However, even though these candidate stations are economically vital or viable, some factors, such as urban planning restrictions, residents' safety concerns, and so on, still play a critical part in the final construction decision. In addition, the framework feasibility was verified through a case study of Guiyang, but a numerical benchmark test of the gridded AP was not performed. All these unconsidered aspects are limitations of this paper. Therefore, for further research, more general factors, especially non-economic factors, are planned to be considered to develop a comprehensive decision. Moreover, the location and sequential expansion of electric bus stations would be analyzed by providing numerical verification tests.

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