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RESEARCH ARTICLE

Improved Bayesian Best-Worst Networks With Geographic Information System for Electric Vehicle Charging Station Selection

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ABSTRACT Electric vehicle charging stations (EVCSs) are essential for solving the energy consumption and endurance anxiety problems of car owners. EVCSs also promote sustainable development in urban economies without relying on fossil fuels. This research proposes a hybrid approach that integrates the Bayesian network with best-worst method (BN-BWM) and a geographical information system (GIS) to address the site selection problem for electric vehicles (EVs). BN-BWM is employed to address the indicator system, which consists of nine criteria from three aspects. BN-BWM calculates the final distribution of the total preference of all decision-makers. Then, a GIS is utilized for spatial analysis and superposition analysis to determine appropriate sites for charging stations (CSs). The novelty of this study lies in the development of a new decision-making method based on the combination of BN-BWM and a GIS. This method is not only more innovative but also highly operational and convincing regarding the accuracy of the weight results. This research provides feasible and reliable ideas for the site selection and construction of CSs. It can also help EV companies and government personnel carry out strategic planning. The study verified the applicability and effectiveness of the developed hybrid method in sixteen administrative regions in Beijing. According to the results, 1) an indicator system consisting of nine criteria is established, and roads, charging stations, and slopes are identified as the most sensitive criteria for site selection; 2) Three alternative stations (ASs) are identified as the most suitable sites for the establishment of CSs.

INDEX TERMS Electric vehicle charging station, site selection, Bayesian network, best-worst method, geographic information system, multiple criteria decision-making.

I. INTRODUCTION

The use of fossil fuels and the resulting effects of climate change are pressing global issues. The International Energy Agency (IEA) has recently published a report entitled "Global Energy Review: 2021 Carbon Emissions", which highlights that CO2 emissions from global energy combustion and industrial processes are expected to significantly increase in 2021. The year-on-year growth is expected to be 6% greater than that in 2020, with a total of 36.3 billion tons of CO2 emissions, the highest annual level ever recorded. Research also shows that CO2 emissions from transportation vehicles are responsible for approximately 40% of total CO2 emissions in cities [1]. China, with its rapid economic growth and urbanization, has experienced a significant increase in the number of motor vehicles on its roads. At the end of 2021, the number of motor vehicles in China reached 395 million, including 302 million cars, for an increase of approximately 7% from the previous year's figure. This increase in the number of motor vehicles in China has led to serious traffic

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congestion and has contributed to a range of social problems, such as energy consumption, resource scarcity, and environmental pollution. The automobile industry must take steps to mitigate these issues by developing cleaner, more energy-efficient, and environmentally friendly vehicles.

The International Energy Agency's "Net Zero By 2050" report underscores the key role of the energy sector in achieving zero emissions by 2050. Many countries are promoting electric vehicles (EVs) and building charging infrastructure as a low-carbon solution. EVs use electricity as their primary energy source and convert it to mechanical energy through the engine, producing significantly less pollution than conventional fuel-powered vehicles. As a result, EVs are considered a viable solution for reducing traffic emissions and oil dependence. In summary, promoting EVs as a low-carbon solution is a critical step toward achieving zero emissions by 2050 [2]. The low-carbon economy has become a central focus of China's economic development. EVs, as a critical component of the new energy strategy, have been identified as a strategic emerging industry. In 2021, China registered 2.95 million new energy vehicles, accounting for 11.25% of the total number of newly registered vehicles, an increase of 1.78 million vehicles and 151.61% greater than the number of vehicles registered in the previous year. China's new energy vehicle market is experiencing explosive growth. However, the development of charging infrastructure is a major obstacle to the expansion of the new energy vehicle market [3].

Public charging stations can overcome the limitations of short-range EVs, and their strategic placement can greatly support the growth of private EVs. CS sites typically take into account factors such as population density, traffic stops, and land slope. Identifying appropriate criteria can help researchers better determine the optimal sites for CSs, expand their coverage and reduce construction costs. Therefore, understanding CS selection and identifying key construction factors can help researchers discover their relationship and provide reliable suggestions to local governments. This approach will promote the growth of the industry and have a significant impact on sustainable urban development, energy conservation, and emission reduction.

This paper proposes a BN-BWM-GIS method for identifying suitable sites for EVCSs. The approach involves selecting the best and worst principles and comparing them with other principles to create a preference aggregation matrix for individual decision-makers. The Bayesian model is then used to determine the weight consistency of the preference aggregation matrix, resulting in the best weight for group decision-making. In addition, an indicator system consisting of three aspects and nine criteria is established to determine the constraint range and value coefficient of the nine criteria. A standard data model of the nine criteria is developed in ArcGIS software, and the weight calculated by the BN-BWM model is employed for superposition analysis to identify the most appropriate sites for constructing CSs. The proposed method provides a comprehensive and effective approach for urban energy conservation and emission reduction efforts and has significant potential for improving the work of existing managers. This study presents a novel GIS-based, BN-BWM site selection priority survey model as its main contribution. The model establishes an indicator system, quantifies the constraint range and value coefficients of the criteria, uses a GIS for spatial analysis, determines the weight through the BN-BWM method, and ranks the results using TOPSIS in the whole evaluation process. The proposed model improves existing methods and provides a comprehensive and effective approach for urban energy conservation and emission reduction managers. The results of this study have significant implications for urban energy conservation and emission reduction work.

The remainder of this paper is organized as follows: Section II provides a review of previous research on existing methods for electric vehicle charging station (EVCS) sites. Section III proposes a hybrid approach that integrates the BN-BWM and GIS models. Section IV establishes a comprehensive index system that consists of three aspects and nine criteria and discusses the meaning and value coefficient of each criterion. Section V uses a case study in the Beijing area to demonstrate the model's operation. Section VI discusses the BN-BWM model results. Section VII provides conclusions and recommendations for future research.

II. LITERATURE REVIEW

The site selection problem for CSs can be addressed using three different methods: (1) multiple criteria decision-making (MCDM),(2) heuristic algorithms, and (3) computational and analytical methods in conjunction with GIS technology.

In addressing complex siting decision problems, such as the siting of CSs, MCDM has been fully applied. There are several well-established methods, such as the analytic hierarchy process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the best-worst method (BWM), and the structural equation model (SEM). For example, Liu et al. introduced a fuzzy BWM and distance-based fuzzy entropy weighting method to derive subjective and objective criteria weights for the shared CS siting problem [4]. In addition, Yilmaz and Atan proposed a fuzzy evaluation based on the distance from the average solution (EDAS) in their case study of Istanbul [5].Dang et al. employed the lambda-fuzzy measure method to determine the weights of the first-class criteria and fuzzy VIKOR for ranking in the location selection of island charging stations [6]. Lin et al. proposed a novel picture fuzzy MCDM model to solve the site selection problem for car sharing stations [7]. The traditional MCDM method usually regards each candidate position as independent, ignoring the spatial correlation and mutual influence between the positions.

When faced with many feasible schemes, determining the optimal solution for the site problem can be challenging. In such situations, heuristic algorithms are applied to help users identify global or local optimal solutions. Therefore, heuristic algorithms with strong optimization capabilities are

FIGURE 1. Framework of the BN-BWM-GIS model for EV site selection.

often applied to the electric vehicle charging station (EVCS) site problem. The genetic algorithm (GA), particle swarm optimization (PSO), and integer programming (IP) are some commonly employed heuristic algorithms. For example, Li et al.proposed an improved GA method using a multipopulation genetic algorithm (MPGA) to provide a more feasible location for public CSs, resulting in a total cost reduction of 7.6%. Similarly [8], Zaheer et al. used deep neural networks to train a school dataset and found that the proposed model had an accuracy that reached 82%, which is helpful for selecting school locations in urban areas [9]. Lan et al. constructed a graph convolutional network (GCN) for learning location problems, providing a new method for solving geographical and transportation problems [10]. Xu et al. proposed an improved nonuniform space ant colony algorithm to address the location of central facilities [11]. In solving the location problem, the heuristic algorithm also has some problems, such as difficult to find the optimal solution, difficult to deal with constraints, difficult to explain and so on

The practicality of EVCSs can be greatly improved by considering geographic information and transportation accessibility, which can be achieved by the application of a GIS. GIS were used for this study to delineate the possible site selection of EVs [12]. Konstantinos et al. proposed a method that uses the AHP and a GIS to determine the optimal site for wind farm installation, followed by ranking of the calculated positions using TOPSIS [13]. This method can help decision-makers overcome conflicting parameters while being economically and environmentally friendly. Rahimi et al. introduced a framework consisting of GIS technology and the fuzzy MCDM method for landfill site selection [14]. A two-phase framework of MCDM methodologies using the merits of Data Envelopment Analysis (DEA), Fuzzy FAHP, and Fuzzy Weighted Aggregated Sum-Product Assessment (FWASPAS) is proposed for the first time. [15].The proposed fuzzy MCDM method is more reliable than other methods in terms of weighting criteria. Adedeji et al. investigated the application of the hexagonal fuzzy MCDM method in EVCSs and demonstrated the effectiveness and robustness of this method by comparative and sensitivity analyses [16]. Karipoglu et al. combined the GIS-MCDM method and hybrid neuro fuzzy modeling tools for site suitability and resource variability forecasting [17]. Moustafa et al. proposed a GIS-based method to determine the best hydrogen charging station locations [18], [19]. In the study of wind farm site selection. The AHP was used to weigh the criteria, and GIS is used to apply the weighted criteria and restrictions [20]. Although some existing methods combining GIS and MCDM have been widely used, there are still some problems, such as inaccurate weight processing.

To address these challenges, a method based on BN-BWM-GIS has been proposed to determine the optimal sites for CSs. Compared to traditional MCDM methods, BN-BWM has great potential in group decision-making and subjective

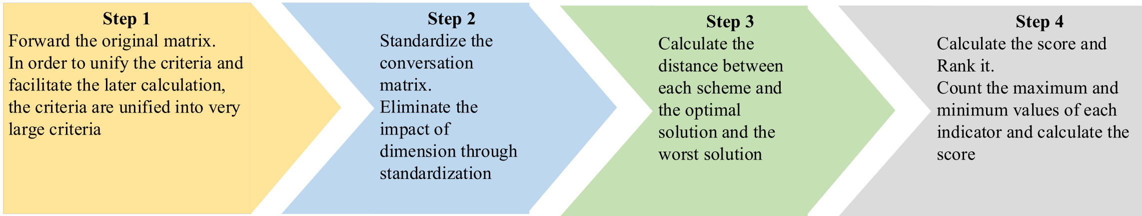

FIGURE 2. TOPSIS ranking.

preference problems and can accurately calculate the group weight distribution. In addition, a GIS can integrate geographic data for spatial analysis and provide visual decision support, enabling decision-makers to make more objective site selections. The TOPSIS method is selected to rank alternative CS sites and assist decision-makers in selecting better sites from a practical point of view.

III. METHODOLOGY

The site selection of EVCSs involves considering the influence of many factors. This research proposes a hybrid method based on BN-BWM-GIS to determine the appropriate sites of CSs. In this section, we introduce the concept of the basic method, and then introduce the integrated model BN-BWM-GIS. **FIGURE1** shows the framework of the BN-BWM-GIS model for EV site selection.

A. BASIC METHODS

1) BWM

The BWM is a multicriteria decision-making (MCDM) method that can be used to solve problems at different stages. The BWM is especially useful for evaluating alternatives based on criteria, particularly when objective criteria are unavailable for evaluating alternatives. The BWM can also be employed to determine the importance of criteria applied to obtain solutions that meet the main objectives of the problem.

In a variety of disciplines, including business and economics, health care, IT, engineering, education, and agriculture, the BWM has been extensively applied to address real-world MCDM issues. In essence, this strategy can be used to rank and choose selections from a group of alternatives. Either a single decision-maker or a group of decision-makers can use the BWM.

2) TOPSIS

TOPSIS is a widely utilized comprehensive evaluation method that effectively utilizes the information from the original data, producing results that accurately reflect the gaps among evaluation schemes. This method is often employed to solve decision-making problems with multiple criteria. Its implementation principle involves sorting and selection options by calculating the relative distance between two alternatives and positive and negative ideal solutions. The main steps involved in TOPSIS are presented as follows:

3) GIS

A GIS, or geographic information system, is a specialized tool for working with spatial data. A GIS is supported by computer software and hardware, enabling it to collect, store, manage, analyze, calculate, display, and describe geographic data on a map. A GIS allows for mapping and analysis of specific events and phenomena in a given area.

B. INTEGRATED BN-BWM-GIS MODEL

1) BN-BWM

The BWM is a multicriteria decision-making (MCDM) method for solving problems at different stages. The BWM is especially useful for evaluating alternatives based on criteria, particularly when objective criteria are unavailable for evaluating alternatives. The BWM can also be used to determine the importance of criteria used to obtain solutions that meet the main objectives of the problem.

Compared with the traditional hierarchical analysis method, the BWM is more convenient and efficient. When there are n evaluation indicators, the traditional method needs to compare all n criteria in pairs, that is, $n(n-1)/2$ pairwise comparisons. However, the BWM only needs $2n-3$ pairwise comparisons.

Although the BWM method is more efficient and convenient than the traditional method in solving MCDM problems, the method can only simultaneously calculate the weighting results of one expert. When there are several experts who need to jointly determine the weights, the weighting results of each expert are often averaged to obtain the final weighting results. However, the process of averaging weights is not good.

A BN is an uncertainty processing model that simulates the causal relationship in the human reasoning process. A BN is well suited for obtaining the interrelationship between knowledge and data and is capable of mining the latent knowledge in the data. Therefore, a BN can well represent the probabilistic relationship between expert decision results and weighted results in this study. We suggest that inserting a BN into the traditional BWM model will have an unexpected effect, helping us solve the group decision problem and providing the degree of accuracy in weight calculation. The detailed implementation steps and inference steps of BN-BWM are listed as follows:

Step 1: The set of criteria for the decision system is determined.

Decision-makers or experts develop n criteria $\{c_1, c_2, \ldots c_n\}$ used in decision issues.

Step 2: The best and worst criteria are selected

According to the n criteria developed in Step 1, the best criteria c_B and worst criteria c_W $(c_B, c_W \in \{c_1, c_2, \ldots, c_n\})$

TABLE 1. Basic scale of paired comparison in BN-BWM.

Verbal scale	Numerical values
Equally important, likely or preferred	1
Moderately important, likely or preferred	3
Strongly more important, likely or preferred	5
Very strongly more important, likely or preferred	7
Extremely more important, likely or preferred	9
Intermediate values to reflect compromise	2, 4, 6, 8

are selected. The best and worst criteria are the key factors affecting the analysis results.

Step 3: c_B is compared with other indicators $c_j (j = 1, 2, \ldots, n)$ in the pair comparison, with numbers 1∼9 indicating the importance degree. **TABLE 1** shows the details. The comparison results are expressed as a vector

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \tag{1}$$

where $a_{Bj} (j = 1, 2, \ldots, n)$ indicates the degree of importance of c_B compared to other indicators $c_j (j = 1, 2, \ldots, n)$

Step 4: Similar to Step 3, c_W is compared with other indicators c_j, and the importance is expressed by numbers 1∼9. The comparison results are expressed as

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW}) \tag{2}$$

where $a_{jW} (j = 1, 2, \ldots, n)$ indicates the importance degree of other indicators c_j compared to c_W.

Step 5: The optimal group weights of the criteria are calculated.

The input values A_W and A_B of the original BWM are constructed as a probability model of multinomial distribution. Since the contents of both vectors are positive integers, the probability mass density function of a multinomial distribution of A_W is

$$P(A_W|w) = \frac{(\sum_{j=1}^{n} a_{jW})!}{\prod_{j=1}^{n} a_{jW}!} \prod_{j=1}^{n} w_j^{a_{jW}} \tag{3}$$

where w is the probability distribution and a_{jW} is the number of times an event occurs.

Equation (4) shows that the probability of events in the multinomial distribution is positively related to the number of events, that is,

$$w_j \propto \frac{a_{jW}}{\sum_{i=1}^{n} a_{iW}}, \quad \forall j = 1, \ldots, n \tag{4}$$

where $\sum_{i=1}^{n} a_{iW}$ is the total number of events.

Similarly, because of the opposite probability distribution, the worst criterion is written as

$$w_W \propto \frac{a_{jW}}{\sum_{i=1}^{n} a_{iW}} = \frac{1}{\sum_{i=1}^{n} a_{iW}} \tag{5}$$

Using Equations (4) and (5), we obtain

$$\frac{w_j}{w_W} \propto a_{jW}, \quad \forall j = 1, \ldots, n, \tag{6}$$

As previously stated, A_B can be modeled using multinomial distribution. However, A_B is different from A_W since the former indicates the preferences of the best criterion over the other criteria, while the latter represents the preferences of the other criteria over the worst criterion. Therefore, A_B demands the inverse of the weight, and $A_B \sim multinomial(1/w)$.

where $1/w$ is the opposite of w.

Similar to the worst criterion, we write

$$\frac{1}{w_j} \propto \frac{a_{Bj}}{\sum_{i=1}^{n} a_{Bi}}, \frac{1}{w_B} \propto \frac{a_{BB}}{\sum_{i=1}^{n} a_{Bi}} = \frac{1}{\sum_{i=1}^{n} a_{Bi}}$$
$$\Rightarrow \frac{w_B}{w_j} \propto a_{Bj}, \quad \forall j = 1, \ldots, n, \tag{7}$$

We have established that the input of the BWM can be converted to a probabilistic form. Consequently, the process of obtaining the final weight in the ordinary BWM problem can be transformed into a probability estimation. The final output results must meet the requirements of nonnegativity and normalization. To establish the weight model, the Dirichlet distribution is employed. The parameter $\alpha \in R^n$ ($\alpha > 0$), where w is defined as the weight of the Dirichlet distribution, is established. $B(\alpha)$ is the normalization constant of the Dirichlet distribution.

$$Dir(w|\alpha) = \frac{1}{B(\alpha)} \prod_{j=1}^{n} w_j^{\alpha_j - 1} \tag{8}$$

Step 6: Construction of joint probability distribution for group decision-making

In this step, k experts, $k = 1, \ldots, K$, evaluate the criteria $c_1, c_2, \ldots, c_n$ by providing the vectors A_B^K and A_W^K. The individual optimal weight after each expert is evaluated is expressed as w^k. Then, the group weight after integration is w^{agg}. $A_B^{1:K}$ denotes the vector of all experts' evaluations of the best criterion compared to the other criteria. Similarly, $A_W^{1:K}$ denotes the vector of all experts' evaluations of the other criteria compared to the worst criterion. These two vectors are the necessary information to construct the joint probability distribution. Thus, the following joint probability distribution is sought.

$$P(w^{agg}, w^{1:K} | A_B^{1:K}, A_W^{1:K}) \tag{9}$$

If the probability in Equation (9) is computed, then the probability of each individual variable is computed using the following probability rule:

$$P(x) = \sum_{y} P(x, y) \tag{10}$$

where $x$and y are two arbitrary random variables.

Step 7: Bayesian hierarchy model development and calculation

In a Bayesian network, the variables are represented as nodes in a graph. As a convention, the observed variables, which are the inputs to the original BWM, are represented as rectangles. The circular nodes represent the variables that need to be estimated. The arrows between the nodes indicate the direction of dependence between them, with the node at the origin being dependent on the node at the destination, that is, the value of w^k is dependent on A_W^K and A_B^K, and the value of w^{agg} is also dependent on w^k. All decision-makers have only one w^{agg}, and each decision-maker will iterate the corresponding variables. Different variables are conditionally independent. For example, A_W^K is independent of w^{agg} given w^k, i.e.,

$$P(A_W^K|w^{agg}, w^k) = P(A_W^K, w^k) \tag{11}$$

Because variables are conditionally independent, Bayesian application in joint probability (7) is expressed as follows:

$$\begin{aligned} &P(w^{agg}, w^{1:K}|A_B^{1:K}, A_W^{1:K}) \\ &\quad \propto P(|A_B^{1:K}, A_W^{1:K}|w^{agg}, w^{1:K})P(w^{agg}, w^{1:K}) \\ &\quad = P(w^{agg})\prod_{k=1}^{K} P(A_W^K|w^k)P(A_B^K|w^k)P(w^k|w^{agg}) \end{aligned} \tag{12}$$

Equation (12) is obtained based on the probability chain rule, the independence between two variables and the preference of each DM.

We now need to specify the distributions of each and every element in Equation (12). We have already shown that A_B and A_W can be perfectly modeled using the multinomial distribution in the sense that it preserves the underlying idea of the BWM. There is only one difference between A_B and A_W since the former shows the preference of all the criteria over the worst criterion, while the latter shows the preference of the best criterion over all the other criteria. Thus, we can model them as

$$\begin{aligned} A_B^K|w^k &\sim multinomial(1/w^k), \quad \forall k = 1, \ldots, K, \\ A_W^K|w^k &\sim multinomial(w^k), \quad \forall k = 1, \ldots, K, \end{aligned} \tag{13}$$

Given w^{agg}, one can expect that each and every w^k will be in proximity. We reparameterize the Dirichlet distribution with respect to its mean and a concentration parameter. The models of w^k given w^{agg} are

$$w^k|w^{agg} \sim Dir(\gamma \times w^{agg}), \quad \forall k = 1, \ldots, K, \tag{14}$$

where w^{agg} is the mean of the distribution and γ is the concentration parameter.

The equation in (14) denotes that the weight vector w^k associated with each DM must be in the proximity of w^{agg} since it is the mean of the distribution, and their closeness is governed by the nonnegative parameter γ. Such a technique is also employed in different Bayesian models. The concentration parameter also needs to be modeled using a distribution. A reliable option is the gamma distribution, which satisfies the nonnegativity constraints, i.e., $\gamma \sim gamma(a, b)$
where a and b are the shape parameters of the gamma distribution.

We supply the prior distribution over w^{agg} using an uninformative Dirichlet distribution with the parameter α as $w^{agg} \sim Dir(\alpha)$.

The BN-BWM model proposed in this paper is an upgrade of the traditional BWM model. While the inputs for both methods remain the same, the optimization problem is replaced with a probabilistic model. This proposed model offers more comprehensive information regarding the confidence of the relation between each pair of criteria. This additional information is obtained through the development of a new Bayesian test, which is based on the approximated distribution from the model.

2) BN-BWM-GIS

As EVCSs are public charging facilities, they need to be rationally planned on the existing urban layout, and the convenience, economy and reasonableness of construction should be considered. Most of the literature does not consider the spatial perspective to facilitate site selection. To ensure the validity and usefulness of the BN-BWM model, we use a GIS as the final site selection tool and use the weighting results of the BN-BWM model to identify alternative sites suitable for establishing EVCSs.

The construction of EVCSs is influenced by many factors, such as geographical conditions, economic level, and traffic accessibility. A GIS is employed in this study to integrate and analyze relevant geographic data. Appropriate sites for EVCSs can be obtained using technologies for spatial analysis and overlay analysis. Many relevant data can be obtained via open source websites and public databases.

Using Beijing as an example, relevant vector files such as administrative districts and roadways in Beijing can be downloaded from http://www.csdn.net. In addition, the Gaode open platform (http://lbs.amap.com) provides access to current data on the distribution of CSs, parking lot distribution, and other relevant data. Beijing's administrative division map is depicted in **FIGURE2.**

This study constructs many map layers for each criterion using ArcGIS software to conduct spatial analysis. After performing distance analysis and reclassification processes, the weighted sum from the toolbox was applied to create the final pixel map. This process enables the selection of appropriate sites for CSs.

In the BN-BWM-GIS model proposed in this paper, the Bayesian model is embedded on the traditional BWM model, which transforms the optimization problem into a probability problem and can well solve the group decision problem and calculate the index weights. The GIS method, which provides a better choice for site selection from a spatial perspective and visual analysis for this paper's research, is incorporated.

IV. MODEL DEVELOPMENT

A. ESTABLISHED CRITERIA HIERARCHY

This study focuses on measuring preferences in alternative site selection by the use of nine criteria, which are grouped

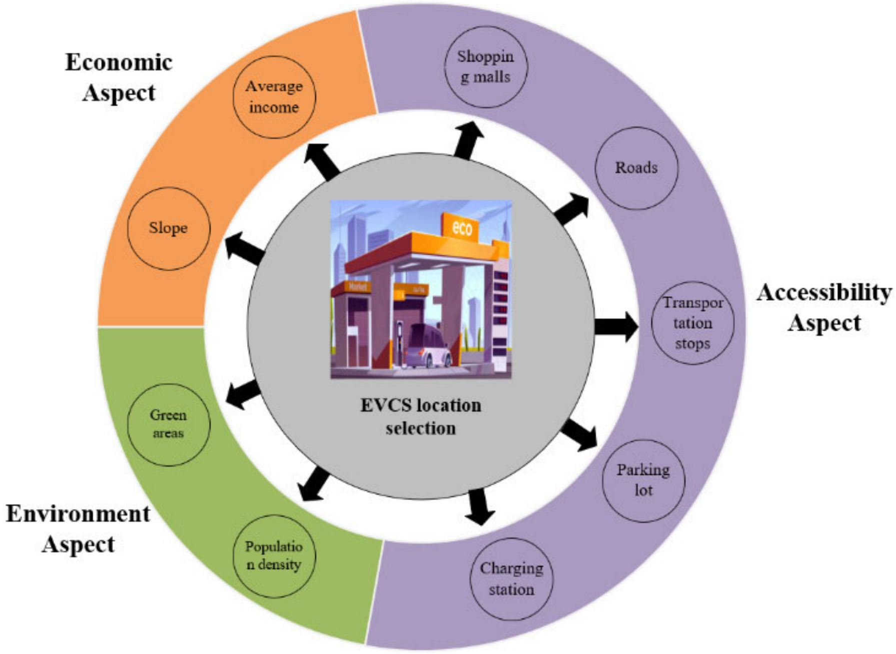

FIGURE 3. Established criteria hierarchy of this study.

into three aspects: accessibility, environment and economy. Each of these aspects plays a significant role in determining the suitability of a particular site. Below, we provide a detailed description of the influential criteria within each aspect.

B. CRITERIA SYSTEM

1) ACCESSIBILITY ASPECT

a: SHOPPING MALLS

Shopping centers comprise a crucial criterion that influences CS sites, as they provide car owners with the opportunity to consume after parking and charging. Proximity to a shopping center is a significant factor in determining the suitability of a site for building a CS. To evaluate this criterion, a vector layer of shopping centers is established within the ArcGIS software, and the reclassification tool is utilized.

b: ROADS

When considering the placement of a CS, it is essential to take into account the convenience of the traffic flow for EVs on the road. Thus, proximity to a main road is a crucial criterion in determining the suitability of a site for a CS. To evaluate this criterion, road layer vector data are obtained, and the road layer is established and accordingly evaluated.

c: TRANSPORTATION STOPS

Transportation stops, such as subway stations and bus stops, are critical transportation hubs that impact the suitability of a site for a CS. The proximity to these stops is an essential criterion, as it determines the convenience of car owners in transferring to other vehicles after charging. To evaluate this criterion, the transportation stops layer is established and evaluated in ArcGIS.

d: PARKING LOTS

Parking is a crucial factor that car owners must consider when selecting a CS site. To evaluate this criterion, public parking lot data in Beijing are obtained via the Gaode development platform, and the parking lot layer is established. Proximity to a parking lot is a critical criterion, as it determines the suitability of a site for building a CS.

e: CHARGING STATIONS

In addition to proximity to various facilities, the coverage and cost of a CS must also be considered when selecting a site for a CS. The suitability of a site for a new CS is determined by its distance from an existing CS. To evaluate this criterion, the distribution of existing CSs in Beijing is obtained from the Gaode development platform. In general, the farther a site is from an existing CS, the more suitable it is for building a new CS.

2) ENVIRONMENTAL ASPECTS

a: POPULATION DENSITY

Population density is another critical factor to consider when selecting a site for a CS. As a general rule, the higher the population density is, the greater the potential for EV usage. To evaluate this criterion, the latest data from the Beijing Municipal Bureau of Statistics are employed to calculate the population density of each district. Sites with higher population densities are considered more suitable for building a CS.

b: GREEN AREAS

In addition to proximity to various facilities and population density, green environmental protection factors must also be considered when selecting a site for a CS. To evaluate this

TABLE 2. Sub-criteria and references for each criterion.

Aspect	Criteria	Description	References
B1. Accessibility	C1. Shopping malls	Number and site of shopping centers in the coverage area.	Guler et al. [21]
	C2. Roads	Road routes in the covered area.	Guler et al.
	C3. Transportation stops	Number and sites of subway stations and bus stops in the coverage area.	Guler et al.
	C4. Parking lot	Number and sites of public parking lots in the covered area.	Guler et al.
B2. Environmental	C5. Charging station	Number and sites of charging stations in the coverage area.	Mahdy , M(2022)
	C6. Population density	Population density per unit land area in the covered area. Unit: person/km^2	Mahdy , M[22]
	C7. Green areas	Number and sites of parks in the coverage area.	Guler et al.
B3. Economic	C8. Slope	Steep and gentle degree of land in the covered area. Unit: degree	Mahdy , M
	C9. Average income	Per capita income in the coverage area. Unit: ¥10000	Guler et al.

criterion, the distance from green areas, such as existing parks in Beijing, is calculated. As a general rule, the farther a site is from green areas, the more suitable it is for building a CS. This condition is determined using the natural breaks method, which assigns a higher value to sites farther from park areas.

3) ECONOMIC ASPECTS

a: SLOPE

Slope is another crucial factor to consider when selecting a site for a CS. Slope affects both the construction cost and difficulty of building a CS. Generally, sites with higher slopes are more expensive to construct and present greater construction challenges. Thus, lower slopes are considered more suitable for building a CS. To evaluate this criterion, the grid layer is established based on the 30 m elevation data of Beijing, and the slope layer is obtained via slope analysis.

b: AVERAGE INCOME

Average income is another critical factor to consider when selecting a site for a CS. Generally, regions with higher average incomes are more likely to have higher rates of EV ownership. To evaluate this criterion, the average income data are obtained from the statistical yearbook of Beijing in 2021. Average income is calculated by dividing the regional GDP by the regional population. Sites with higher average incomes are considered more suitable for building a CS.

TABLE 2 presents the subcriteria and references for each criterion. Note that the limitations of each criterion will be considered based on global experience and expert studies, as explicit provisions may not be available. These restrictions are then applied to ArcGIS software for evaluation purposes.

V. CASE STUDY

This study focuses on Beijing to demonstrate the effectiveness of the BN-BWM site model based on a GIS. By the end of 2020, the number of new energy vehicles in Beijing had reached 400,000, with a goal of reaching a total of 2 million by 2025 and increasing the car electrification rate from 6% to 30%. However, the existing CS infrastructure in Beijing and throughout China often suffers from unreasonable layouts and structures, leading to slow and difficult charging processes. In response, Beijing has implemented policies to strengthen the construction of charging infrastructure, as outlined in various policy documents.

The steps to solve the problem of strategy selection are as follows:(1) Invite 6 domestic experts with rich experience in the field of new energy vehicles to assist in identifying 10 influencing factors according to the BWM method. The expert teams are from NIO (2 people), China Association of Automobile Manufacturers (2 people), and School of Automotive, Hefei University of Technology (2 people). Recognition is based on two considerations: industry status and existence; (2) Invite 6 experts to assist in weight measurement through scoring survey. We collected the suggestions of experts and selected the 9 influencing factors discussed above as the criteria for evaluating the location of EVCS (3) Consider the relationship between factors; (4) BN-BWM-GIS was used to calculate the global weight of each strategy, and finally the overall ranking of each strategy was obtained. The specific steps are as follows:

Step 1 (Calculation of the group decision weight using BN-BWM): The flow chart for determining the final BN-BWM method is shown in **FIGURE1**.BWM model is more efficient and convenient than traditional methods in solving MCDM problems, and BN model can deal with expert knowledge in BWM model well and convert it into accurate value through probability relation. The language scale of the BN-BWM model, which allows the decision-maker's preference to be transformed into a computable scale and accurately determines the standard weight,

TABLE 3. Experts' preference degrees of the three aspects and the resultant optimal weights.

	Experts panel	Best criteria	Worst criteria	Preferences achieved from 6 experts				
				C1	C2	C3	C4	C5
Accessibility aspect	Expert1	C5	C1	(6,5)	(4,7)	(5,6)	(5,5)	(4,9)
	Expert2	C5	C3	(5,6)	(6,8)	(4,5)	(5,5)	(4,7)
	Expert3	C5	C1	(5,4)	(4,8)	(5,5)	(6,4)	(4,6)
	Expert4	C5	C1	(7,4)	(5,7)	(5,6)	(5,5)	(4,8)
	Expert5	C3	C4	(7,4)	(6,7)	(4,4)	(5,4)	(6,6)
	Expert6	C2	C4	(7,5)	(4,5)	(6,8)	(6,4)	(5,5)
	Weight			**0.1641**	**0.2292**	**0.2028**	**0.1719**	**0.232**
				C6	C7			
Environmental aspect	Expert 1	C6	C7	(5, 8)	(5, 4)			
	Expert 2	C6	C7	(4, 6)	(6, 4)			
	Expert 3	C6	C7	(5, 6)	(7, 7)			
	Expert 4	C7	C6	(7, 5)	(4, 6)			
	Expert 5	C6	C7	(5, 7)	(9, 4)			
	Expert 6	C6	C7	(5, 5)	(7, 5)			
	Weight			**0.5499**	**0.4501**			
				C8	C9			
Economic aspect	Expert 1	C9	C8	(7, 5)	(6, 7)			
	Expert 2	C9	C8	(5, 8)	(4, 5)			
	Expert 3	C8	C9	(4, 5)	(8, 5)			
	Expert 4	C9	C8	(6, 6)	(4, 6)			
	Expert 5	C9	C8	(8, 9)	(4, 4)			
	Expert 6	C8	C9	(4, 7)	(5, 6)			
	Weight			**0.5141**	**0.4859**			

TABLE 4. Weighting by BN-BWM evaluation criteria for EVCS.

Aspect	B1. accessibility					B2. environmental		B3. economic	
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Weight	0.0933	0.1289	0.1146	0.0971	0.1307	0.1159	0.0945	0.1162	0.1090

is presented in **TABLE 1** [22]. In this experiment, there were six decision-makers. The expert preferences corresponding to the criteria were input into MATLAB software to calculate the final aggregation matrix. **TABLE 3** shows the weights of the accessibility, environmental, and economic aspects after the BN-BWM model calculation. The weight values of the nine criteria were determined and are presented in **TABLE 4**. The weight values obtained were consistent with the expected values, which demonstrated the superiority and reliability of the BN-BWM methods.

Step 2 (Weighted suitability analysis for EVCSs based on ArcGIS): In this study, nine criteria suitability map layers were established in ArcGIS software, and initial data processing was conducted for each criteria map layer. **FIGURE4** shows the nine criteria suitability map layers established in ArcGIS software. Note that the subcriteria of C1, C2, C3, C4, C5, and C7 refer to the distance between them in meters. The unit of C6 is person/km^2, and its subcriteria refer to the population density of 16 administrative regions in Beijing. The unit of C8 is degrees, and the subcriteria describe the gradient of land in Beijing. The unit of C9 is 10000 RMB

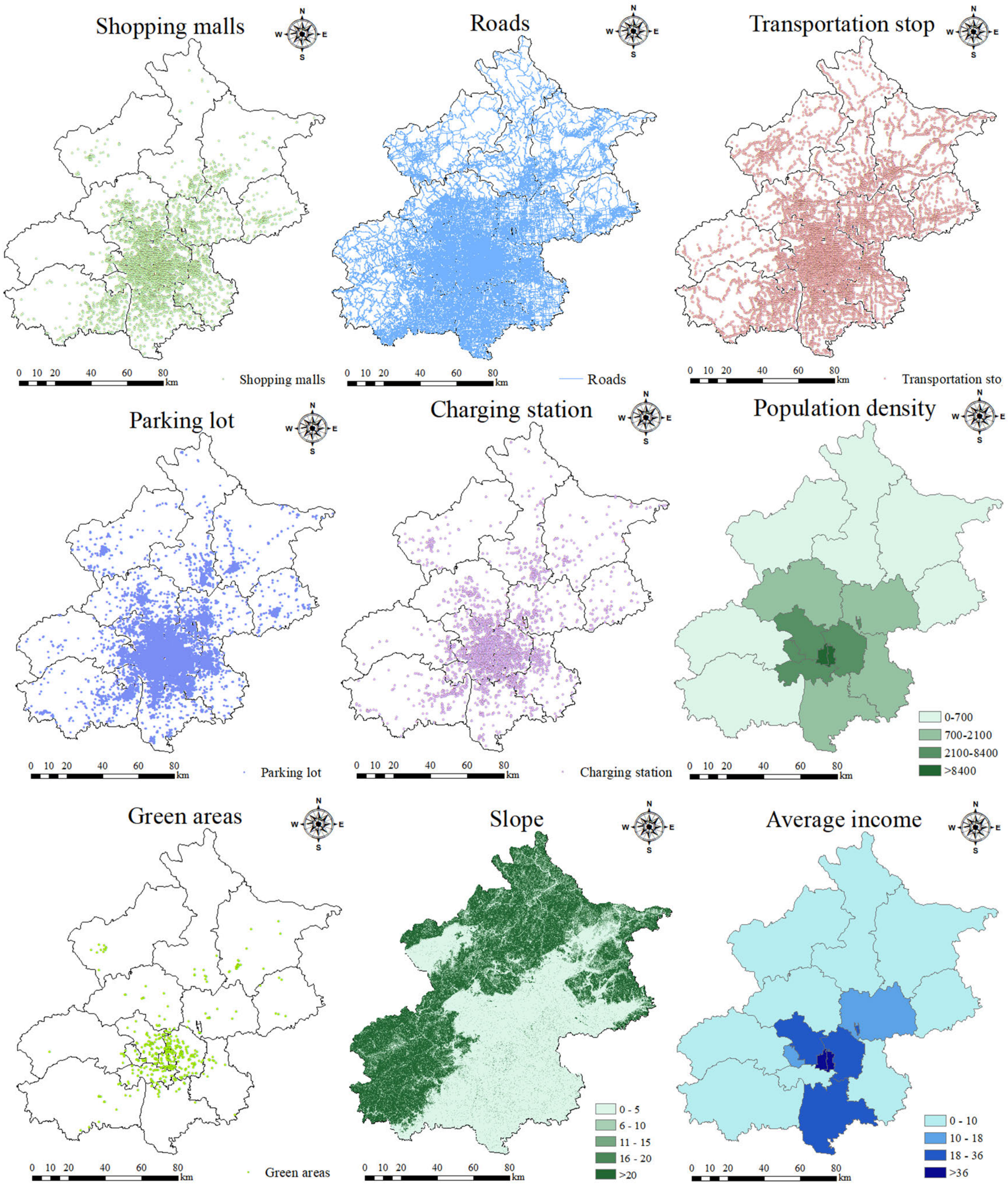

FIGURE 4. Map layer corresponding to nine criteria in ArcGIS.

Yuan, and the subcriteria refer to the income level of residents in 16 administrative regions of Beijing.

As shown in **FIGURE5**, ArcGIS software was used to classify layers, cover nine criteria adaptive layers, and generate maps of three aspects (accessibility, environmental, and economic) using the weighted sum tool.

Step 3 (Generation of alternate EVCSs): **TABLE 4** displays the weight values for the normalized final gather matrix. Using the ArcGIS toolbox, the weighted sum of nine criteria applicability layers is utilized to derive the final suitability evaluation layer of EVCSs, as illustrated in **FIGURE6**. The red areas indicate the most suitable sites for building EVCSs, while the blue areas are the least suitable sites for building EVCSs. Following the principle of average distribution and maximum coverage of the CS area, sixteen alternative sites are chosen from the final suitability assessment map as potential sites for EVCSs. **TABLE 5** lists the specific coordinates of the sixteen chosen sites for EVCSs.

Step 4 (Computation of the subordinate and final rankings): In this section, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is employed to rank the candidate sites for EVCSs and identify the most suitable site. The sixteen candidate sites are evaluated based on the TOPSIS criteria, with their respective weights presented in

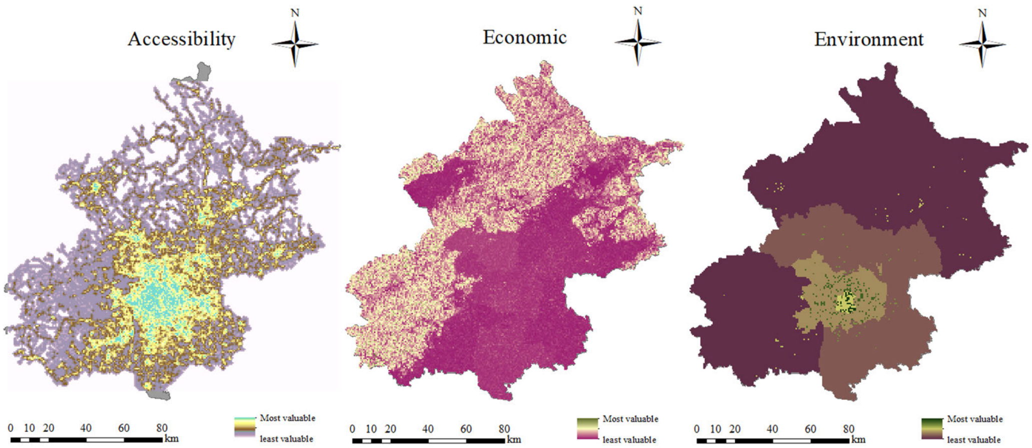

FIGURE 5. Accessibility map, environmental map, and economic map.

TABLE 5. Sixteen AS sites for EVCSs.

FID	Point_X	Point_Y	FID	Point_X	Point_Y
AS1	413114.792	4480236.218	AS9	457008.192	4406558.011
AS2	434277.681	4455154.275	AS10	464846.299	4419490.888
AS3	442899.599	4436734.723	AS11	442899.599	4402247.052
AS4	443683.41	4420274.698	AS12	426047.669	4402247.052
AS5	448386.274	4423801.847	AS13	470332.974	4442613.304
AS6	448778.179	4415963.74	AS14	469157.258	4464168.098
AS7	456224.381	4426153.279	AS15	486792.999	4471222.395
AS8	456224.381	4417531.361	AS16	509915.415	4446140.452

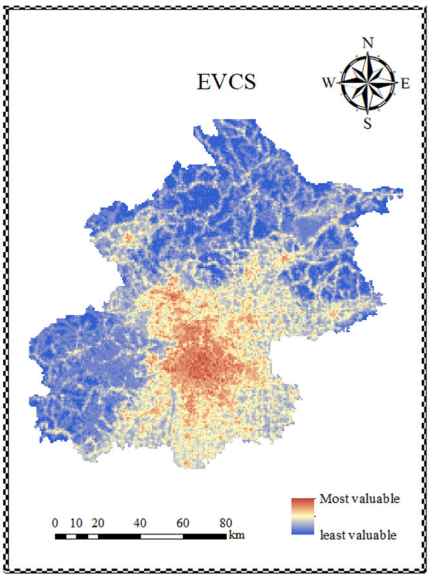

FIGURE 6. Evaluation map of EVCSs.

TABLE 6. The TOPSIS method is then applied to sort the candidate sites based on pixel value and CS distribution. In the research area, the pixel value refers to the density information of the region, while the CS distribution relates to the distance from the existing CS, specifically, the maximum distance between the alternative CS and the existing CS. The precise value is derived from the distance analysis tool provided by ArcGIS.

TABLE 6. TOPSIS criteria and their respective weights.

Criteria	Units	Importance	Goal
Pixel values	px	8	Maximize
CS distance	m	5	Maximize

Step 5 (Discussion of the results): TABLE 7 presents the ranking of the alternative sites with equal weight, while **FIGURE7** displays the ranking of the alternative sites based on accessibility weight.

VI. DISCUSSION OF THE RESULTS

To select an appropriate alternative site, the BN-BWM results are projected onto a matrix consisting of four quadrants. **FIGURE8** displays the four quadrants based on the BN-BWM weighted rating results on the X-axis (with higher scores on the right) and the coverage area of the optional construction area on the Y-axis (with a higher range at the top). The coverage area of the optional construction area is

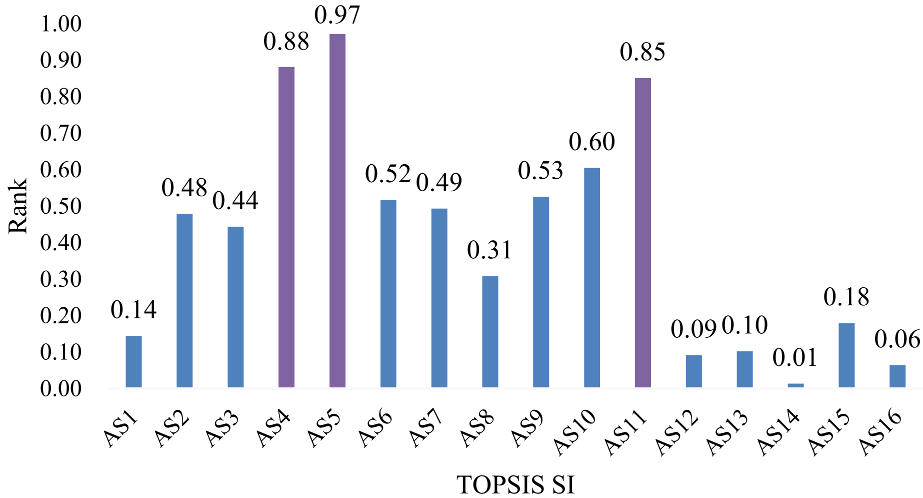

FIGURE 7. AS Ranks by TOPSIS.

TABLE 7. Ranking of alternative stations according to equal weights.

Rank	1	2	3	4	5	6	7	8
FID	AS5	AS4	AS11	AS10	AS9	AS6	AS7	AS2
Di+	0.0002	0.0008	0.0009	0.0025	0.0031	0.0032	0.0033	0.0034
Di-	0.0073	0.0073	0.0065	0.0049	0.0043	0.0043	0.0041	0.0040
Si	0.9772	0.9030	0.8786	0.6595	0.5839	0.5753	0.5518	0.5377
Rank	9	10	11	12	13	14	15	16
FID	AS3	AS8	AS15	AS12	AS13	AS12	AS16	AS14
Di+	0.0037	0.0047	0.0058	0.0061	0.0065	0.0065	0.0068	0.0074
Di-	0.0037	0.0027	0.0016	0.0013	0.0009	0.0008	0.0006	0.0001
Si	0.5022	0.3603	0.2168	0.1759	0.1260	0.1132	0.0801	0.0173

determined based on the final suitability assessment map, as shown in **FIGURE6**.

A. ATTRACTIVE AREA

The first quadrant represents the candidate sites with large coverage areas and high scores (AS4, AS5, and AS6). The optional construction area in this quadrant covers a large region and has a high score, rendering it more suitable for establishing the EVCS to complete the local charging network. We refer to this quadrant as the ''attractive area.''

B. LOW-POTENTIAL AREA

The second quadrant, the ''low-potential area,'' contains only one alternative site, AS7, with a low-ranking score but a large coverage area. Therefore, it is not recommended as the first choice for CS construction after the charging system is relatively complete.

C. LESS-PREFERRED AREA

The third quadrant, consisting of nine alternative sites, namely, AS1, AS2, AS3, AS8, AS13, AS14, AS15, and AS16, has not only a small optional construction area but also a low score and is therefore named the ''less-preferred area.'' We included all 16 potential sites in the profile matrix, and the resulting rankings were classified into the four quadrants, as shown in **FIGURE8**.

D. HIGH-VALUE AREA

The optional construction area in the fourth quadrant has low coverage but a high score and is thus named the ''high-value area.'' Three alternative sites, AS9, AS10, and AS11, have small coverage areas but high TOPSIS ranking scores. These sites should be considered in CS construction planning, as they are ideal construction sites.

According to **FIGURE6**, the alternative site where the first quadrant is located has great potential. Dongcheng District and Xicheng District of Beijing, for example, are prime sites. First, they have excellent traffic conditions, ensuring that car owners can easily pass after parking and charging. Second, while some charging networks already exist in these areas, there is a need for additional charging stations to cater to the high population flow and charging demand. Last, the

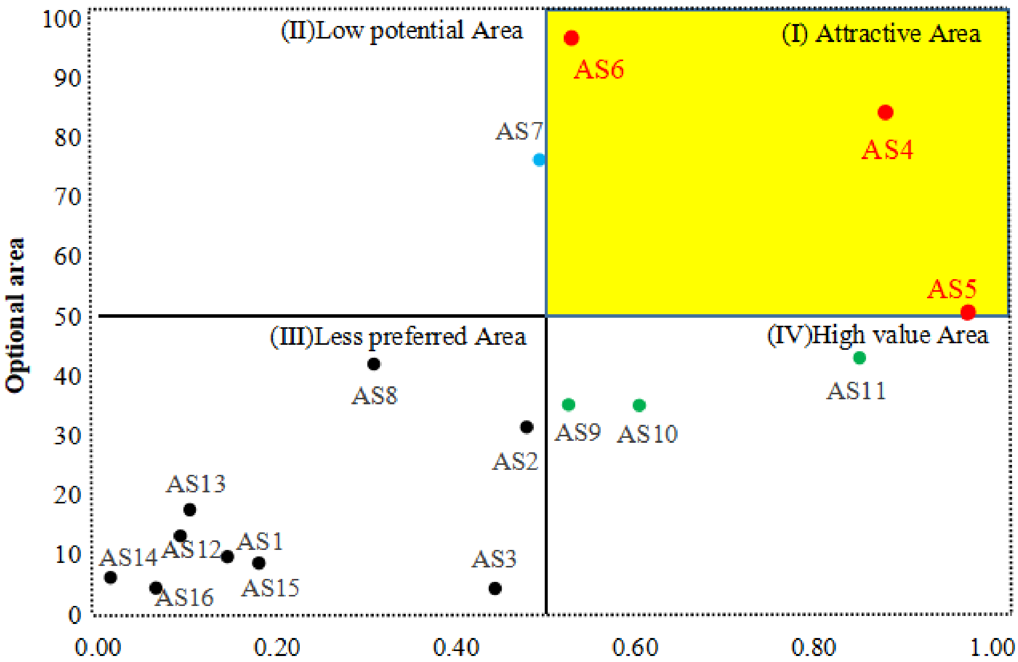

FIGURE 8. Evaluation profile of the potential AS site selection.

slope factor is a crucial determinant of the cost of building a charging station. Due to their flat terrain, these districts are more suitable for building charging stations.

Although the low-potential area (second quadrant) has excellent accessibility, it falls short in terms of environmental and economic factors. While the traffic in this area is relatively developed, the slope and greening criteria are still at lower average levels. Additionally, the local economic development lags behind that of other regions, and people are generally hesitant to purchase relatively expensive electric vehicles. As a result, it is not recommended to establish a charging station in this area.

The third quadrant's less desirable site is remote and lacks unique qualities, making it unadvisable to establish alternative sites in this area when compared to more favorable sites.

Ultimately, the fourth quadrant is considered a high-value area due to its high TOPSIS score. In comparison to economically underdeveloped regions, the payment capacity for electric vehicles is relatively high in these areas. Moreover, the flat land, convenient transportation, and strong accessibility of these areas ensure that their charging demand remains consistently high. Therefore, based on our analysis results, we recommend the establishment of charging stations in this area to improve the local charging network and meet the charging needs of local residents.

VII. CONCLUSION AND FUTURE RESEARCH

CSs are considered an effective solution to the confusion and difficulties of urban charging systems. However, the existing CS infrastructure in Beijing falls short of meeting the growing demand for charging and is far from government planning. This study is aimed at evaluating appropriate sites for EVCSs by considering accessibility, environmental, and economic aspects. The study provides a systematic decision-making framework, integrating expert opinions to effectively select and rank CS sites. The study's main contributions include providing a systematic evaluation framework for CS sites using nine qualitative and quantitative criteria based on accessibility, environmental, and economic factors. Additionally, the study employs BN-BWM to calculate the weight of the indicator system, while the GIS tool is utilized to determine an appropriate CS site. The TOPSIS method is applied, considering the practicability and effectiveness to calculate the ranking of candidate sites. Overall, this study's findings can help policy-makers and urban planners make informed decisions when selecting sites for CSs. By employing the evaluation framework, decision-makers can identify the most suitable sites based on several criteria, resulting in a more efficient charging infrastructure.

This study has yielded interesting findings from different perspectives. First, AS4, AS5, and AS6 were identified as the most suitable alternatives for CS sites. Second, the weight calculation results revealed that road quality, charging station availability, and slope were the most sensitive factors impacting the construction of CSs. Third, accessibility was identified as the most crucial aspect affecting the construction of CSs.

This paper also has some shortcomings: a) Beijing is limited as a survey area, because its charging facilities have been relatively well established; b) the selection range of experts is narrow and the number of experts is small.

For further development of this study, several aspects could be considered. First, other multicriteria decision-making (MCDM) methods, such as the AHP and VIKOR, could be explored to compare and validate the results obtained using BN-BWM and TOPSIS. Second, the standard system could be updated to incorporate policy support, charging time, and other relevant criteria that were not considered in this study due to limited information access. Third, other methods, such as buffer zone analysis, could be employed instead of distance analysis to address subcriteria requirements in GIS software. Last, fuzzy methods, such as the fuzzy BWM, could be employed to enhance the accuracy and effectiveness of CS site selection. By considering these aspects, future research could build on the findings of this study to further improve the efficiency of urban charging systems.

Competing interests The authors declare no competing interests.

REFERENCES

[1] *Global Energy Review: CO2 Emissions in 2021, Global Emissions Rebound Sharply to Highest Ever Level*, Int. Energy Agency (IEA), Paris, France. 2022. Accessed: Sep. 8, 2022. [Online]. Available: https://www.iea.org/news/global-co2-emissions-rebounded-to-their-highest-level-in-history-in-2021

[2] *Net Zero By 2050*, Int. Energy Agency (IEA), Paris, France, 2021. Accessed: Sep. 9, 2022. [Online]. Available: https://www.iea.org/reports/net-zero-by-2050

[3] Y. Zhang, Q. Zhang, A. Farnoosh, S. Chen, and Y. Li, "GIS-based multi-objective particle swarm optimization of charging stations for electric vehicles," *Energy*, vol. 169, pp. 844–853, Feb. 2019.

[4] A. Liu, Y. Zhao, X. Meng, and Y. Zhang, "A three-phase fuzzy multi-criteria decision model for charging station location of the sharing electric vehicle," *Int. J. Prod. Econ.*, vol. 225, Jul. 2020, Art. no. 107572.

[5] M. Yılmaz and T. Atan, "Hospital site selection using fuzzy EDAS method: Case study application for districts of Istanbul," *J. Intell. Fuzzy Syst.*, vol. 41, no. 2, pp. 2591–2602, Sep. 2021.

[6] R. Dang, X. Li, C. Li, and C. Xu, "A MCDM framework for site selection of island photovoltaic charging station based on new criteria identification and a hybrid fuzzy approach," *Sustain. Cities Soc.*, vol. 74, Nov. 2021, Art. no. 103230.

[7] M. Lin, C. Huang, and Z. Xu, "MULTIMOORA based MCDM model for site selection of car sharing station under picture fuzzy environment," *Sustain. Cities Soc.*, vol. 53, Feb. 2020, Art. no. 101873.

[8] J. Li, Z. Liu, and X. Wang, "Public charging station location determination for electric ride-hailing vehicles based on an improved genetic algorithm," *Sustain. Cities Soc.*, vol. 74, Nov. 2021, Art. no. 103181.

[9] N. Zaheer, S.-U. Hassan, M. Ali, and M. Shabbir, "Optimal school site selection in urban areas using deep neural networks," *J. Ambient Intell. Humanized Comput.*, vol. 13, no. 1, pp. 313–327, Jan. 2022, doi: 10.1007/s12652-021-02903-9.

[10] T. Lan, H. Cheng, Y. Wang, and B. Wen, "Site selection via learning graph convolutional neural networks: A case study of Singapore," *Remote Sens.*, vol. 14, no. 15, p. 3579, Jul. 2022, doi: 10.3390/rs14153579.

[11] Q. Xu, L. Zhang, and W. Yu, "A localization method of ant colony optimization in nonuniform space," *Sensors*, vol. 22, no. 19, p. 7389, Sep. 2022, doi: 10.3390/s22197389.

[12] I. S. Bayram, U. Zafar, and S. Bayhan, "Could petrol stations play a key role in transportation electrification? A GIS-based coverage maximization of fast EV chargers in urban environment," *IEEE Access*, vol. 10, pp. 17318–17329, 2022.

[13] I. Konstantinos, T. Georgios, and A. Garyfalos, "A decision support system methodology for selecting wind farm installation locations using AHP and TOPSIS: Case study in eastern macedonia and thrace region, Greece," *Energy Policy*, vol. 132, pp. 232–246, Sep. 2019.

[14] C.-N. Wang, T.-T. Dang, and N.-A.-T. Nguyen, "Location optimization of wind plants using DEA and fuzzy multi-criteria decision making: A case study in Vietnam," *IEEE Access*, vol. 9, pp. 116265–116285, 2021.

[15] Ö. Kaya, K. D. Alemdar, T. Campisi, A. Tortum, and M. K. Çodur, "The development of decarbonisation strategies: A three-step methodology for the suitable analysis of current EVCS locations applied to istanbul, Turkey," *Energies*, vol. 14, no. 10, p. 2756, May 2021.

[16] P. A. Adedeji, S. A. Akinlabi, N. Madushele, and O. O. Olatunji, "Hybrid neurofuzzy investigation of short-term variability of wind resource in site suitability analysis: A case study in south Africa," *Neural Comput. Appl.*, vol. 33, no. 19, pp. 13049–13074, Oct. 2021, doi: 10.1007/s00521-021-06001-x.

[17] F. Karipoğlu, M. S. Genç, and B. Akarsu, "GIS-based optimal site selection for the solar-powered hydrogen fuel charge stations," *Fuel*, vol. 324, Sep. 2022, Art. no. 124626.

[18] Y. S. R. Moustafa, M. S. Abdalzaher, M. Naeem, and M. M. Fouda, "Seismic hazard and site suitability evaluation based on multicriteria decision analysis," *IEEE Access*, vol. 10, pp. 69511–69530, 2022.

[19] D. Guler and T. Yomralioglu, "Suitable location selection for the electric vehicle fast charging station with AHP and fuzzy AHP methods using GIS," *Ann. GIS*, vol. 26, no. 2, pp. 169–189, 2020, doi: 10.1080/19475683.2020.1737226.

[20] M. Mahdy, A. S. Bahaj, P. Turner, N. Wise, A. S. Alghamdi, and H. Hamwi, "Multi criteria decision analysis to optimise siting of electric vehicle charging points—Case study Winchester district, U.K.," *Energies*, vol. 15, no. 7, p. 2497, Mar. 2022.

[21] J. Zhou, Y. Wu, C. Wu, F. He, B. Zhang, and F. Liu, "A geographical information system based multi-criteria decision-making approach for location analysis and evaluation of urban photovoltaic charging station: A case study in Beijing," *Energy Convers. Manage.*, vol. 205, Feb. 2020, Art. no. 112340.

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