An Integrated Multi-Criteria Decision Making Approach to Location Planning of Electric Vehicle Charging Stations

Hu-Chen Liu, *Member, IEEE*, Miying Yang, MengChu Zhou, *Fellow, IEEE*, and Guangdong Tian, *Member, IEEE*

***Abstract*—Electric vehicles (EVs) are recognized as one of the most promising technologies worldwide to address the fossil fuel energy resource crisis and environmental pollution. As the initial work of EV charging station (EVCS) construction, site selection plays a vital role in its whole life cycle, which, however, is a complicated multiple criteria decision making (MCDM) problem involving many conflicting criteria. Therefore, this paper aims to propose a novel integrated MCDM approach by a grey decision making trial and evaluation laboratory (DEMATEL) and uncertain linguistic multi-objective optimization by ratio analysis plus full multiplicative form (UL-MULTIMOORA) for determining the most suitable EVCS site in terms of multiple interrelated criteria. Specifically, the grey DEMATEL method is used to determine criteria weights and the UL-MULTIMOORA model is employed to evaluate and select the optimal site. Finally, an empirical example in Shanghai, China, is presented to demonstrate the applicability and effectiveness of the proposed approach. The results show that the proposed approach is a useful, practical, and effective way for the optimal location of EVCSs.**

***Index Terms*—Electric vehicle, site selection, uncertain linguistic variables, MULTIMOORA, multiple criteria decision making.**

I. Introduction

WITHs the rapid urbanization development and increasing demand on automobiles, energy shortage and air pollution have gained much attention from the countries around the world. In China, the transportation sector contributes 20-30% of the total national energy consumption, as well as 7% of the gross emissions of carbon dioxide [1]. Among many innovative solutions, *electric vehicles* (EVs) are considered as a promising mobility alternative to reduce energy consumption and *greenhouse gas* (GHG) emission [2]. Meanwhile, EVs, can promote the stable and economic operation of electric power grids via shifting power peak load, providing spinning reserve and improving the penetration of renewable energy power [3]. In past years, the Chinese government took various policies and regulations to promote the use of EVs, and allocated considerable funding to subsidize EV manufacturers and buyers [4], [5].

Public charging stations, as the energy provider for EVs, are significant in promoting the development of EV industry [1]. Lacking convenient and efficient charging infrastructure, consumers will not buy EVs because of their shorter driving range and range anxiety [6], [7]. In the *EV charging station* (EVCS) construction, determining the optimal site is a quite important stage, which greatly impacts service quality and operational efficiency of the established facilities. Improper selection of sites will adversely affect an EVCS's safety and benefits during normal operations. Therefore, the emerging question for engineers and planners is where to locate EVCSs to serve various charging demands of a city [8]–[11].

Selection of the best site for an EVCS can be regarded as a complicated *multiple criteria decision making* (MCDM) problem, which often involve many conflicting criteria, such as operational benefit, effects on ecological environment, and harmonization between EVCS and urban development [8]. MULTIMOORA (*Multi-objective optimization by ratio analysis plus full multiplicative form*) is a method newly developed by Brauers and Zavadskas [12] to deal with MCDM problems. It is more comprehensive than other MCDM methods since it consists of three different parts, i.e., the ratio system, the reference point and the full multiplicative form. Besides, the MULTIMOORA can facilitate a decision making process and provide effective rankings [13]–[15]. Recently, it has been applied in a number of fields for various purposes [13], [15]–[17]. However, its use within the EVCS site selection framework was not accomplished before. Therefore, this work intends to develop an extended MULTIMOORA method to determine the optimal location of EVCSs under an uncertain linguistic context.

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On the other hand, there may exist complicated and interrelated relationships between evaluation criteria in a practical EVCS site selection. *Decision-making trial and evaluation laboratory* (DEMATEL) [18], [19] is an effective method to analyze the inter-relationships among system factors and visualize them by using a cause-effect relationship diagram. Moreover, it is capable of dividing interrelated criteria and dimensions into cause and effect groups [20]. Since its introduction, the DEMATEL method has been successfully applied in various fields [21]–[27]. Given its strengths, this paper will utilize the DEMATEL to model the dependency among EVCS site selection criteria and further determine their relative weights.

With the motivations stated above, this work proposes an integrated MCDM approach based on grey DEMATEL and uncertain linguistic MULTIMOORA (UL-MULTIMOORA) to optimally locate public charging stations for EVs. The main contributions of this study are threefold: First, the theory of uncertain linguistic variables is used to manage the decision makers' uncertain and diverse linguistic assessments. Second, the causal relationships and interaction levels among evaluation criteria are addressed using the grey DEMATEL method. Third, with the UL-MULTIMOORA model, the proposed approach can get a robust ranking of candidate sites and identify the best one to implement a public EVCS. Finally, an empirical example is presented to demonstrate the potential and advantages of the proposed EVCS site selection framework.

The rest of this paper is structured as follows: We review the EVCS locating literature and indicate research gaps in Section II. The basic definitions and concepts of grey theory and uncertain linguistic variables are recalled in Section III. A hybrid MCDM approach is developed in Section IV for the EVCS site selection. Section V examines the feasibility and effectiveness of the proposed approach by applying it to a practical case. Finally, main conclusions and future directions of this research are presented in Section VI.

II. Literature Review

Depending on various objectives, a number of MCDM-based location models have been proposed in the literature. On the one hand, multi-objective decision making (MODM) techniques have been applied for site selection especially for the deployment of public charging infrastructures. For example, Tu *et al*. [7] developed a spatial-temporal demand coverage approach for optimizing the placement of electric taxi charging stations considering temporal constraints such as electric taxi range, charging time, and capacity of charging stations. He *et al*. [28] incorporated institutional and spatial constraints, such as local government requirements on charging facility deployment and spatial distribution of potential sites, into facility location models. Shahraki *et al*. [29] proposed an optimization model based on vehicle travel data to capture public charging demand and applied it to Beijing, China by maximizing the amount of vehicle-miles-traveled being electrified. Cavadas et al. [30] developed an improved mixed integer programming model for locating slow-charging stations for EVs in urban areas accounting for driver tours. You and Hsieh [31] developed a mixed-integer programming model to handle the location problem of vehicle charging stations under budget restrictions and, Sadeghi-Barzani et al. [32] developed a mixed-integer non-linear optimization model to determine the optimal place and size of fast EVCSs by considering station development cost, EV energy loss, electric gird loss as well as the location of electric substations and urban roads. Liu et al. [33] used a two-step screening method to identify the optimal site of EVCSs and developed a mathematical model with the minimization of total cost associated with EVCSs. Xu *et al*. [34] established a mathematical model that determines the optimal placement of charging infrastructures under the condition of large-scale integration of pure EVs into grid. Wang and Lin [35] applied the concepts of set-and maximum-coverage to formulate a mixed integer programming method for locating multiple types of recharging stations for battery-powered EV transport.

On the other hand, multiple attribute decision making (MADM) methods have been used to solve the site selection problems arose from different scenarios. For instance, Zhao and Li [1] employed a fuzzy *grey relation analysis* (GRA)-VIKOR method for optimal siting of EVCSs from an extended sustainability perspective. Wu *et al*. [11] used a *preference ranking organization method for enrichment evaluations* (PROMETHEE)-based decision making system combined with cloud model for the site selection of EVCSs. Guo and Zhao [8] applied fuzzy *technique for order of preference by similarity to ideal solution* (TOPSIS) approach for selecting the most sustainable site of EVCSs considering environmental, economic and social criteria. Awasthi *et al*. [36] adopted the fuzzy TOPSIS method to evaluate and select the best location for implementing an urban distribution center under uncertainty. Vasileiou *et al*. [37] presented a geographical information system-based decision making model for the site selection of hybrid offshore wind and wave energy systems, in which *analytical hierarchy process* (AHP) was used to identifying the most appropriate marine area. Govindan *et al*. [38] established an integrated approach to identify preferred facility locations, in which AHP was used to determine the weights of criteria and TOPSIS was utilized to find the preference order of available locations. Gigović *et al*. [39] suggested a spatial multi-criteria model for the selection of sites for ammunition depots by using the DEMATEL-based ANP technique and the *multiattributive ideal-real comparative analysis* (MAIRCA) method. In addition, a hybrid method of *interpretive structural modelling* (ISM), fuzzy AHP, and fuzzy TOPSIS was given in [40] for selecting a sustainable location of healthcare waste disposal facility, and an attitudinal-based interval 2-tuple linguistic VIKOR method was proposed in [41] to select the best disposal site for municipal solid waste.

The above literature review indicates several issues related to EVCS site selection researches. First, parameters in the location models are fixed numbers and known in advance. In reality, however, the parameters may not be obtained with certainty. Moreover, uncertain linguistic evaluations are often given by experts because of time pressure and lack of data. Uncertain linguistic variables can be used to overcome the above limitations and are more flexible and good at describing uncertain linguistic information. Second, previous studies have generally considered evaluation criteria as independent when establishing site selection models. However, in many real-world cases, there may exist complicated and interrelated relationships among criteria. DEMATEL is an effective method for analyzing causal relationships among factors and structuring them through graphical representations. Third, researchers have used a variety of MCDM methods for ranking alternative sites, but there has been no complete integration method to provide sufficient ranking information during site selection processes. MULTIMOORA represents one of the most robust approaches to multi-objective optimization. Therefore, the purpose of this study is to fill these gaps by extending the MULTIMOORA method based on uncertain linguistic variables for the evaluation and selection of EVCSs. Further, the grey DEMATEL technique is utilized to determine the weights of criteria by considering their interactions.

III. Preliminaries

A. Grey Theory

The grey theory was proposed by Deng [42] to handle the ambiguities in cases of discrete data and incomplete information [43], [44]. Its basic concepts can be defined as follows.

Definition 1: Let x be a closed and bounded set of real numbers, a grey number $\otimes$ is defined as an interval with known upper and lower bounds but unknown distribution information for x [42]. That is,

$$\otimes x = [\underline{x}, \bar{x}] = \left[x' \in x \,\middle|\, \underline{x} \le x' \le \bar{x}\right], \tag{1}$$

where $\underline{x}$ and $\bar{x}$ represent the lower and upper bounds of $\otimes x$, respectively.

Definition 2: Give any two grey numbers $\otimes x_1 = \left[\underline{x}_1, \bar{x}_1\right]$, $\otimes x_2 = \left[\underline{x}_2, \bar{x}_2\right]$ and let λ be a crisp number, the basic mathematical operations of grey numbers are expressed as follows [44]:

$$\otimes x_1 + \otimes x_2 = \left[\underline{x}_1 + \underline{x}_2, \bar{x}_1 + \bar{x}_2\right], \tag{2}$$

$$\lambda \times \otimes x_1 = \left[a\underline{x}_1, a\bar{x}_1\right]. \tag{3}$$

Definition 3: A set of grey numbers $\otimes x_j = \left[\underline{x}_j, \bar{x}_j\right] (j = 1, 2, \ldots, n)$can be easily converted into crisp values by the converting fuzzy data into crisp scores (CFCS) method, following the procedure described as follows:

(1) Normalize the grey numbers

$$\underline{x}_j = \frac{\left(\underline{x}_j - \min\limits_j \underline{x}_j\right)}{\Delta_{\min}^{\max}}, \tag{4}$$

$$\bar{x}_j = \frac{\left(\bar{x}_j - \min\limits_j \underline{x}_j\right)}{\Delta_{\min}^{\max}}, \tag{5}$$

where $\Delta_{\min}^{\max} = \max\limits_j \bar{x}_j - \min\limits_j \underline{x}_j$.

(2) Compute the total normalized crisp values

$$y_j = \frac{\underline{x}_j \left(1 - \underline{x}_j\right) + \bar{x}_j \times \bar{x}_j}{1 - \underline{x}_j + \bar{x}_j}. \tag{6}$$

(3) Compute the final crisp values

$$z_j = \min_j \bar{x}_j + y_j \Delta_{\min}^{\max}. \tag{7}$$

B. Uncertain Linguistic Variables

A finite and ordered discrete linguistic term set is usually introduced as $S = \left\{s_0, s_1, \ldots, s_g\right\}$, where g is an even number, s_i represents a possible value for a linguistic variable, and it satisfies the following characteristics: (1) $s_i > s_j$, if$i > j$, and (2) there is a negative operator $neg\left(s_i\right) = s_{g-i}$.

In many decision making processes, the linguistic rates of decision makers may not match any of the original linguistic terms, and there may be no clear cut between two of them. Thus, Xu [45] extended the discrete linguistic variables to uncertain linguistic variables.

Definition 4: Let $S = \left\{s_0, s_1, \ldots, s_g\right\}$ be a linguistic term set, a uncertain linguistic variable $\tilde{s}$ is defined as [45]:

$$\tilde{s} = \left[s_\alpha, s_\beta\right], \tag{8}$$

where $s_\alpha, s_\beta \in S$, s_α and s_β are the lower and the upper limits of $\tilde{s}$, respectively.

Definition 5: Let $\tilde{s}_1 = \left[s_{\alpha_1}, s_{\beta_1}\right], \tilde{s}_2 = \left[s_{\alpha_2}, s_{\beta_2}\right]$ be any two uncertain linguistic variables and $\lambda \in [0, 1]$ is a crisp number, then their operational laws are displayed as follows [45], [46]:

$$\tilde{s}_1 \oplus \tilde{s}_2 = \left[s_{\alpha_1}, s_{\beta_1}\right] \oplus \left[s_{\alpha_2}, s_{\beta_2}\right] = \left[s_{\alpha_1+\alpha_2}, s_{\beta_1+\beta_2}\right], \tag{9}$$

$$\tilde{s}_1 \otimes \tilde{s}_2 = \left[s_{\alpha_1}, s_{\beta_1}\right] \otimes \left[s_{\alpha_2}, s_{\beta_2}\right] = \left[s_{\alpha_1\times\alpha_2}, s_{\beta_1\times\beta_2}\right], \tag{10}$$

$$\lambda\tilde{s}_1 = \lambda\left[s_{\alpha_1}, s_{\beta_1}\right] = \left[s_{\lambda\alpha_1}, s_{\lambda\beta_1}\right], \tag{11}$$

$$\left(\tilde{s}_1\right)^\lambda = \left[s_{\alpha_1}, s_{\beta_1}\right]^\lambda = \left[s_{\alpha_1^\lambda}, s_{\lambda\beta_1^\lambda}\right]. \tag{12}$$

To make a comparison between uncertain linguistic variables, the concept of possibility degrees is introduced here based on the work of [45].

Definition 6: Let $\tilde{s}_1 = \left[s_{\alpha_1}, s_{\beta_1}\right]$, and $\tilde{s}_2 = \left[s_{\alpha_2}, s_{\beta_2}\right]$ be any two uncertain linguistic variables, and let $d_{\tilde{s}_1} = \beta_1 - \alpha_1$ and $d_{\tilde{s}_2} = \beta_2 - \alpha_2$, then the possibility degrees between them are defined as

$$p\left(\tilde{s}_1 > \tilde{s}_2\right) = \frac{\max\left(0, \beta_1 - \alpha_2\right) - \max\left(0, \alpha_1 - \beta_2\right)}{d_{\tilde{s}_1} + d_{\tilde{s}_2}}, \tag{13}$$

$$p\left(\tilde{s}_2 \ge \tilde{s}_1\right) = \frac{\max\left(0, \beta_2 - \alpha_1\right) - \max\left(0, \alpha_1 - \beta_2\right)}{d_{\tilde{s}_1} + d_{\tilde{s}_2}}. \tag{14}$$

Definition 7: Let $\tilde{s}_1 = \left[s_{\alpha_1}, s_{\beta_1}\right]$ and $\tilde{s}_2 = \left[s_{\alpha_2}, s_{\beta_2}\right]$ be two uncertain linguistic variables, then

1) if $p\left(\tilde{s}_1 > \tilde{s}_2\right) > p\left(\tilde{s}_2 \ge \tilde{s}_1\right)$, then $\tilde{s}_1$ is superior to $\tilde{s}_2$ to the degree of $p\left(\tilde{s}_1 > \tilde{s}_2\right)$, denoted by $\tilde{s}_1 \overset{p(\tilde{s}_1 > \tilde{s}_2)}{\succ} \tilde{s}_2$;
2) if $p\left(\tilde{s}_1 > \tilde{s}_2\right) = p\left(\tilde{s}_2 \ge \tilde{s}_1\right) = 0.5$, then $\tilde{s}_1$ is indifferent to $\tilde{s}_2$, denoted by $\tilde{s}_1 \cong \tilde{s}_2$;
3) if $p\left(\tilde{s}_2 \ge \tilde{s}_1\right) > p\left(\tilde{s}_1 > \tilde{s}_2\right)$, then $\tilde{s}_1$ is inferior to $\tilde{s}_2$ to the degree of $p\left(\tilde{s}_2 \ge \tilde{s}_1\right)$, denoted by $\tilde{s}_1 \overset{p(\tilde{s}_2 \ge \tilde{s}_1)}{\prec} \tilde{s}_2$.

Definition 8: Let $\tilde{s}_1 = \left[s_{\alpha_1}, s_{\beta_1}\right]$ and $\tilde{s}_2 = \left[s_{\alpha_2}, s_{\beta_2}\right]$ be two uncertain linguistic variables, then

$$d\left(\tilde{s}_1, \tilde{s}_2\right) = \sqrt{\frac{1}{3}\left[\left(\alpha_1 - \alpha_2\right)^2 + \left(\beta_1 - \beta_2\right)^2 + \left(\alpha_1 - \alpha_2\right)\left(\beta_1 - \beta_2\right)\right]} \tag{15}$$

is called the distance between $\tilde{s}_1$ and $\tilde{s}_2$.

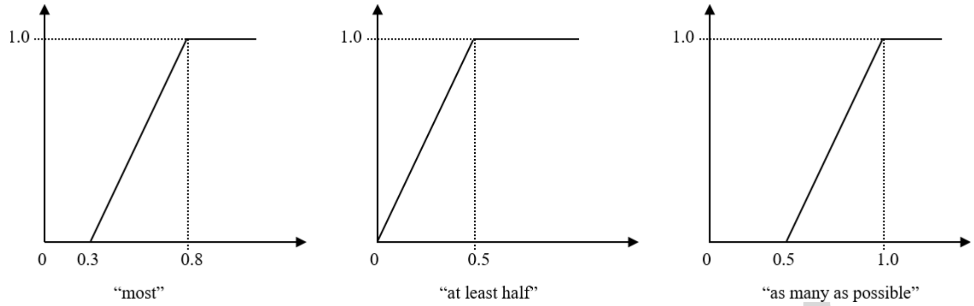

Fig. 1. Proportional linguistic quantifiers.

Definition 9: Let $X = \{\tilde{s}_1, \tilde{s}_2, \ldots, \tilde{s}_n\}$ be a set of uncertain linguistic variables, which has an associated weighting vector $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ such that $w_i \in [0, 1], i = 1, 2, \ldots, n, \sum_{j=1}^{n} w_i = 1$. Then the uncertain linguistic ordered weighted averaging (ULOWA) is described as [45]:

$$\text{ULOWA}(X) = \text{ULOWA}(\tilde{s}_1, \tilde{s}_2, \ldots, \tilde{s}_n) = \mathop{\oplus}_{j=1}^{n} \omega_j \tilde{s}_{\sigma(j)}, \quad (16)$$

where $\tilde{s}_{\sigma(j)}$ denotes the jth largest of the $\tilde{s}_i$ values, $\tilde{s}_i \in S$.

Determining the weight vector ω is crucial in applying the ULOWA operator. Many different methods have been suggested do derive the ordered weighted aggregation (OWA) weights. The most common method is the one guided by the fuzzy linguistic quantifier [46], which can not only allow decision makers to translate their preferences in different ways but also reduce the influence of unduly high or unduly low arguments in the decision making.

Definition 10: The aggregation weighing vector ω is determined based on a non-decreasing proportional linguistic quantifier Q, given by

$$w_j = Q\left(\frac{j}{n}\right) - Q\left(\frac{j-1}{n}\right), \quad j = 1, 2, \ldots, n, \quad (17)$$

$$\text{Q}(y) = \begin{cases} 0 & \text{if } y < a \\ \dfrac{y-a}{b-a} & \text{if } a \le y \le b \\ 1 & \text{if } y > b, \end{cases} \quad (18)$$

with $a, b \in [0, 1]$, and $\text{Q}(y)$ represents the degree to which the proportion y is compatible with the meaning of the quantifier. Some representative non-decreasing proportional linguistic quantifiers are identified by the terms “most”, “at least half”, and “as many as possible”, where the parameters (a, b), are (0.3, 0.8), (0, 0.5) and (0.5, 1), respectively [47]. Fig. 1 shows their membership functions for the sake of visualization.

For example, if four elements are considered and the linguistic quantifier “most” with the pair (0.3, 0.8) is used, then we have

$$\text{Q}(y) = \begin{cases} 0 & \text{if } y < 0.3 \\ \dfrac{y-0.3}{0.8-0.3} & \text{if } 0.3 \le y \le 0.8 \\ 1 & \text{if } y > 0.8 \end{cases}.$$

Applying Eq. (17), the weights are calculated as:

$$\omega_1 = Q\left(\frac{1}{5}\right) - Q(0) = 0, \quad \omega_2 = Q\left(\frac{2}{5}\right) - Q\left(\frac{1}{5}\right) = 0.2,$$

$$\omega_3 = Q\left(\frac{3}{5}\right) - Q\left(\frac{2}{5}\right) = 0.4, \quad \omega_4 = Q\left(\frac{4}{5}\right) - Q\left(\frac{3}{5}\right) = 0.4,$$

and $\omega_5 = Q(1) - Q\left(\frac{4}{5}\right) = 0$.

IV. The Proposed Methodology

In this section, we establish a hybrid MCDM approach by combining grey DEMATEL technique with UL-MULTIMOORA method to solve the EVCS sitting problem with interrelated criteria. The grey DEMATEL is used for analyzing the interrelationships between evaluation criteria and computing the influential weight for each criterion. To select the most suitable site, the UL-MULTIMOORA is adopted to determine the ranking order of the alternative sites. Fig. 2 delineates the flowchart of the proposed approach for EVCS site selection, and the corresponding decision procedures are explained in the following subsections.

A. The Grey DEMATEL for Computing Criteria Weights

The DEMATEL technique is a structural modeling approach to analyze causal-effect relationships among complex factors [18]. In this study, grey theory is integrated with the DEMATEL to examine the interdependent relationships of evaluation criteria for the EVCS site selection problem. Assume that a system contains a set of n criteria $\{C_1, C_2, \ldots, C_n\}$ and an expert group has l respondents $DM_1, DM_2, \ldots, DM_l$, the steps involving the grey DEMATEL are introduced below.

Step 1: Generate the overall grey direct-relation matrix

First, the expert group is asked to pairwise compare the evaluation criteria in terms of an influence comparison scale. For example, a grey linguistic scale including five linguistic terms can be expressed as grey numbers shown in Table I. The results of these evaluations generate l grey direct-relation matrixes $\otimes Z_k = \left[\otimes z_{ij}^k\right]_{n\times n}$, where $\otimes z_{ij}^k$ represents the direct influence of criterion C_i over criterion C_j given by decision maker DM_k. Based on the direct respondent matrices, the overall grey direct-relation matrix $\otimes Z = \left[\otimes z_{ij}\right]_{n\times n}$ can be calculated via the average method.

Step 2: Develop the crisp direct-relation matrix

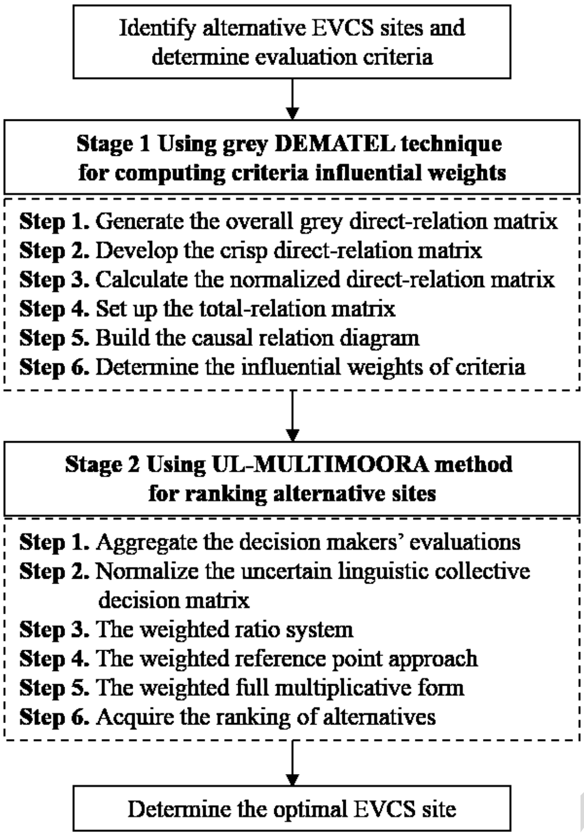

Fig. 2. Flowchart of the proposed EVCS site selection model.

TABLE I
GREY LINGUISTIC SCALE FOR DIRECT-RELATION OF CRITERIA

Linguistic terms	Grey numbers
No influence (N)	[0, 0]
Very low influence (VL)	[0.00, 0.25]
Low influence (L)	[0.25, 0.50]
High influence (H)	[0.50, 0.75]
Very high influence (VH)	[0.75, 1.00]

In this step, the CFCS defuzzification method is used to transform the grey direct-relation matrix $\otimes Z = \left[\otimes z_{ij}\right]_{n\times n}$ into a crisp direct-relation matrix $Z = \left[z_{ij}\right]_{n\times n}$.

Step 3: Obtain the normalized direct-relation matrix

Based on the matrix Z, the normalized direct-relation matrix $X = \left[x_{ij}\right]_{n\times n}$ is obtained through (19)-(20).

$$X = \frac{Z}{s}, \tag{19}$$

where

$$s = \max\left\{\max_{1\le i\le n}\sum_{j=1}^{n} z_{ij},\quad \max_{1\le j\le n}\sum_{i=1}^{n} z_{ij}\right\}. \tag{20}$$

All elements in the matrix X lie between 0 and 1, and the summation of at least one (but not all) row or column equals to 1.

Step 4: Set up the total-relation matrix

The normalized direct-relation matrix X is processed by using (21) to set up the total-relation matrix$T = \left[t_{ij}\right]_{n\times n}$.

$$T = X\left(I - X\right)^{-1}, \tag{21}$$

in which I denotes an identity matrix.

Step 5: Build the causal relation diagram

Based on the matrix$T$, the sum of rows and the sum of columns are expressed as the vectors R and C, respectively.

$$R = [r_i]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1}, \tag{22}$$

$$C = \left[c_j\right]_{n\times 1} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n}^{T}, \tag{23}$$

where r_i is the sum of the ith row in the matrix T and represents the sum of both direct and indirect influences given by criterion C_i towards the other criteria. Likewise, c_j is the sum of the jth column in the matrix T and denotes the sum of both direct and indirect influences received by criterion C_j from the other criteria.

Based on the data set (R+C, R-C), a causal relation diagram can be plotted, where R+C illustrates the degree of importance that the criterion plays in the system and R-C shows the net effect that the criterion contributes to the system.

Step 6: Calculate the influential weights of criteria

The weight vector for evaluation criteria $w = (w_1, w_2, \ldots, w_n)$ is generated by the following equation [48]:

$$w_j = \frac{\sqrt{\left(r_j + c_j\right)^2 + \left(r_j - c_j\right)^2}}{\sum_{j=1}^{n}\sqrt{\left(r_j + c_j\right)^2 + \left(r_j - c_j\right)^2}}. \tag{24}$$

B. The UL-MULTIMOORA for Ranking Alternatives

The MULTIMOORA is a robustness MCDM method, which determines the ranking of alternatives based on dominance theory [12]. In the second stage of the proposed model, the normal MULTIMOORA is extended to the uncertain linguistic environment (called UL-MULTIMOORA) to derive the ranking priority of EVCS sites.

Assuming that an EVCS selection problem has K decision makers $DM_k\,(k = 1, 2, \ldots, K)$, m feasible alternatives $A_i\,(i = 1, 2, \ldots, m)$ and n evaluation criteria $C_j\,(j = 1, 2, \ldots, n)$. Let $\tilde{X}^k = \left[\tilde{x}_{ij}^k\right]_{mn}$ be the uncertain linguistic decision matrix of the kth decision maker, where $\tilde{x}_{ij}^k$ is the rating of alternative A_i pertaining to criterion C_j. In here, the ratings of alternatives are linguistic assessments represented by uncertain linguistic variables $\tilde{x}_{ij}^k = \left[s_{\alpha_{ij}}^k, s_{\beta_{ij}}^k\right]$. Following the grey DEMATEL, the procedures of the UL-MULTIMOORA are continued to find the optimal location for EVCSs.

Step 1: Establish the uncertain linguistic collective decision matrix

By utilizing the ULOWA operator, all decision makers' ratings for alternatives are aggregated to construct the uncertain linguistic collective decision matrix $\tilde{X} = \left[\tilde{x}_{ij}\right]_{m\times n}$, where

$$\tilde{x}_{ij} = \left[s_{\alpha_{ij}}, s_{\beta_{ij}}\right] = \text{ULOWA}\left(\tilde{x}_{ij}^1, \tilde{x}_{ij}^2, \ldots, \tilde{x}_{ij}^K\right). \tag{25}$$

Note that fuzzy linguistic quantifier is adopted in this study to calculate the weights of the ULOWA operator.

Step 2: Normalize the uncertain linguistic collective decision matrix

Considering benefit and cost criteria, the normalized uncertain linguistic decision matrix $\tilde{R} = \left[\tilde{r}_{ij}\right]_{m\times n}$ is computed as

$$\tilde{r}_{ij} = \left[s_{\alpha'_{ij}}, s_{\beta'_{ij}}\right] = \begin{cases} \left[\operatorname{neg}\left(s_{\alpha_{ij}}\right), \operatorname{neg}\left(s_{\beta_{ij}}\right)\right] & \text{for cost criteria} \\ \left[s_{\alpha_{ij}}, s_{\beta_{ij}}\right] & \text{for benefit criteria.} \end{cases} \quad (26)$$

Step 3: The weighted ratio system

In this step, the collective assessments of a certain alternative are added by

$$\tilde{y}_i = \mathop{\oplus}_{j=1}^{n} w_j \tilde{r}_{ij}, \quad (27)$$

where $\tilde{y}_i$ is the overall assessment value of alternative A_i for the weighted ratio system.

Step 4: The weighted reference point approach

A maximal objective reference point (MORP) vector $\tilde{r}^*$ is deduced based on the matrix $\tilde{R} = \left[\tilde{r}_{ij}\right]_{m\times n}$. Since the elements $\tilde{r}_{ij}$ are uncertain linguistic variables belong to the linguistic term set $S = \left\{s_0, s_1, \ldots, s_g\right\}$, we can define the jth coordinate of the MORP vector as $\tilde{r}_j^* = \left[s_g, s_g\right]$. Then, the distance matrix $D = \left[d_{ij}\right]_{m\times n}$ is acquired by

$$d_{ij} = d\left(\tilde{r}_{ij}, \tilde{r}_j^*\right), \quad (28)$$

where d_{ij}denotes the gap of alternative A_i with respect to criterion C_j. The weighted distance of each alternative from the MORP vector is obtained using (29).

$$d_i = \sum_{j=1}^{n} w_j d_{ij}. \quad (29)$$

Step 5: The weighted full multiplicative form

The overall utility of the alternative A_i is an uncertain linguistic variable, which can be computed via

$$\tilde{u}_i = \mathop{\otimes}_{j=1}^{n} \left(\tilde{r}_{ij}\right)^{w_j}. \quad (30)$$

Step 6: Acquire the ranking of alternatives

All the alternatives can be prioritized by arranging the assessment values $\tilde{y}_i$ and $\tilde{u}_i$ for $i = 1, 2, \ldots, m$ in decreasing order, and the assessment values$d_i$for $i = 1, 2, \ldots, m$ in ascending order. Then, the final ranking of the alternatives could be derived by integrating the three sets of rankings with the dominance theory [49].

V. Empirical Example

A. Background

Shanghai is one of the fastest developing cities in China and, because of rapid economy development, vehicle demand has been rising dramatically for many years. In 2016, the number of cars in Shanghai reached 3.22 million, ranking the top fourth in China. Similar to others Chinese cities, air pollution is a growing problem in Shanghai. Hence, Shanghai government is endeavoring to promote the use of EVs and construct more and more charging infrastructures. It is expected that by 2020, EV production and sales in Shanghai exceeded 20, 000 vehicles, and there will build 68 charging stations and 12, 000 charging piles. Based on market demands and government support, an electricity company plans to build a charging station for EVs in Shanghai. By reviewing project feasibility research reports [4], [5] and the Shanghai development planning, a total of four sites are determined as alternatives for EVCSs, which are located in the districts of Minghang (A_1), Jiading (A_2), Baoshan (A_3), and Pudong (A_4), respectively. These alternatives, with typical characteristics of a large residential community, are suitable for constructing EV charging facilities. Fig. 3 displays the geographical locations of these sites. For evaluating the EVCS sites comprehensively, many qualitative and quantitative factors should be taken into account. The evaluation criteria for the optimal location of EVCSs are selected from the perspective of economic sustainability. The sustainability theory requires a new development way which can achieve economic growth and social development without environmental damage. Sustainability has three dimensions: environment, economy and society. Therefore, the evaluation index system for EVCS site selection includes these three dimensions. Further, the relevant criteria affiliated with these dimensions are determined according to [8], [11], [50], and expert interviews. The final evaluation index system comprising three dimensions and nine criteria is shown in Table II.

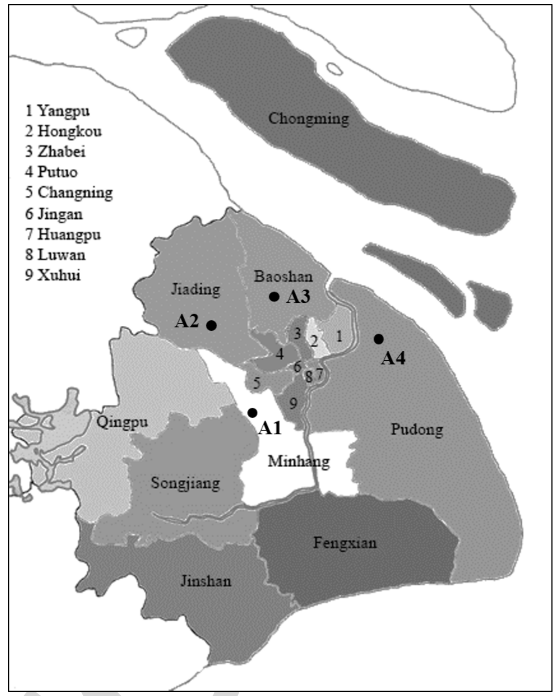

Fig. 3. Geographical locations of the alternative sites.

In this study, the evaluations on the weights of criteria and on the alternatives over each criterion are conducted by five expert groups, denoted as DM_1, $DM_2, \ldots, DM_5$. The assessment panels are comprised of experts in the fields of environment, economy, industrial engineering, electric power system and transportation system. Besides, all invited experts should have a master degree and more than three years relevant working experience as their basic qualifications. Because of

TABLE II
EVALUATION INDEX SYSTEM FOR THE CASE STUDY

Dimensions	Evaluation criteria	Explanations	Types
Environment (D_1)	Destruction degree on vegetation and water (C_1)	Measures the vegetation deterioration and water loss due to the land development for building EVCS	Cost
	Waste discharge (C_2)	Measures the construction garbage as well as sewage discharged during the EVCS construction, and the wastewater effluent due to the vehicle cleaning and battery disposal during the EVCS operation	Cost
	Air pollutants reduction (C_3)	Measures the environmental pollutants (such as CO2 and PM2.5) emission reduction by using EV rather than ICEV	Benefit
Economy (D_2)	Construction cost (C_4)	Includes land cost, demolition cost, equipment acquisition cost, and project investment cost	Cost
	Annual operation and maintenance cost (C_5)	Includes electric charge, staff wages, financial expenses, tax, battery amortization, and so on	Cost
Society (D_3)	Harmonization of EVCS with the development planning of urban road network and power grid (C_6)	Coordination with main artery, inlet and outlet, residential areas, urban main functional areas, and the stable supply of electric power	Benefit
	Traffic convenience (C_7)	Main road condition, number of vehicles lane, and number of intersections near the EVCS location	Benefit
	Service capability (C_8)	Number of EV that can get access to the charging service provided by EVCS, the daily charging volume, and the maximum charging volume	Benefit
	Adverse impact on people's lives (C_9)	Adverse impacts of noise and electromagnetic field due to the construction and operation of EVCS on the daily life of local residents	Cost

TABLE III
INITIAL DIRECT-RELATION MATRICES PROVIDED BY E EXPERT GROUPS

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	-	VL,H,VL,L,L	VL,L,L,L,VL	L,H,H,L,H	L,H,L,H,L	VL,L,L,VL,L	VL,VL,VL,VL,VL	L,L,VL,L,VL	VH,H,VH,H,VH
C_2	VH,H,H,H,VH	-	VH,L,L,L,L	H,H,L,H,L	H,H,H,H,H	L,L,L,VL,H	VL,L,L,L,VL	VL,L,L,L,VL	VH,H,VH,H,VH
C_3	H,L,VL,VL,L	VL,L,VL,VL,L	-	H,H,H,H,H	H,VL,H,H,L	VL,L,L,VL,L	VL,L,VL,VL,L	VL,L,L,VL,L	VH,VH,VH,VH,VH
C_4	VH,H,H,H,VH	VH,L,H,L,H	VH,H,VH,VH,H	-	H,H,H,H,H	H,H,H,H,H	L,L,L,H,L	VH,VH,VH,VH,H	VH,H,H,H,H
C_5	VH,H,H,VH,H	VH,H,VH,VH,H	VH,L,H,VH,H	VL,N,VL,VL,N	-	L,H,H,L,H	L,L,VL,VL,L	H,H,VH,H,H	VH,L,H,H,VH
C_6	VL,H,H,L,H	VL,L,H,L,VL	VL,H,H,H,L	H,H,H,H,L	H,H,H,VH,L	-	H,L,L,L,H	VH,L,VH,VH,H	L,H,H,H,L
C_7	VL,VL,VL,VL,VL	VL,VL,L,L,VL	VL,H,H,L,H	H,L,L,L,L	H,H,L,L,H	H,L,L,L,H	-	VH,H,H,VH,H	L,L,H,L,H
C_8	VH,L,L,L,VL	VH,H,H,H,H	VH,VH,VH,VH,VH	H,VH,H,VH,H	H,VH,H,H,VH	VL,L,H,L,L	VL,L,L,L,VL	-	H,H,H,H,H
C_9	L,L,L,VL,L	L,L,L,L,L	L,L,L,L,VL	H,L,H,L,H	H,L,H,H,L	VL,L,L,VL,L	VL,L,L,L,VL	H,L,H,L,H	-

the difficulty to assess the influence among criteria precisely, the grey linguistic scale defined in Table I is used for comparing the evaluation criteria. In addition, experts' questionnaires are collected as inputs to determine the ratings of alternatives with the linguistic term set S,

$$S = \{s_0 = Very\ Low\,(VL)\,, s_1 = Low\,(L)\,, s_2 = Moderately\ Low\,(ML)\,, s_3 = Medium\,(M)\,, s_4 = Moderately\ High\,(MH)\,, s_5 = High\,(H)\,,\ s_6 = Very\ High\,(VH)\}\,.$$

The decision makers in each expert group gave their own evaluations first based on the general information of alternative sites. Then they met to make a final assessment according to the collective results. Consequently, the linguistic evaluations collected from the five expert groups for criteria interdependencies and for the alternative sites are listed in Tables III-IV, respectively.

B. Implementation

In the sequence, the procedure of the proposed hybrid approach is implemented to determine the most suitable EVCS site.

First, the grey DEMATEL technique is utilized to analyze the interrelationships between criteria. After converting into corresponding grey numbers, the individual grey direct-relation matrixes from Table III are combined to construct the overall grey direct-relation matrix $\otimes Z$. Then, the crisp direct-relation matrix Z is obtained with the CFCS method. Based on (19)-(20) the normalized direct-relation matrix X is calculated, and by (21), the total-relation matrix T is obtained as shown in Table V. Additionally, the influences given and received on criteria are summarized in Table VI, and the causal relation diagram is plotted as displayed in Fig. 4. Note that the arrows representing significant relationships among criteria based on the threshold of 0.369, which is calculated by adding one standard deviation to the mean of the values in matrix T. Finally, the criteria weights are determined by using (24) and listed in Table VI.

Next, the UL-MULTIMOORA method is employed to obtain the ranking of the EVCS sites. First, the linguistic evaluations given in Table IV are transformed into uncertain linguistic decision matrices $\tilde{X}^k = \left[\tilde{x}_{ij}^k\right]_{4\times 9}$ $(k = 1, 2, \ldots, 5)$. Then, by (25), the uncertain linguistic collective decision matrix $\tilde{X} = \left[\tilde{x}_{ij}\right]_{4\times 9}$ is yielded and presented in Table VII.

TABLE IV
LINGUISTIC RATINGS OF ALTERNATIVES PROVIDED BY EXPERT GROUPS

Expert groups	Alternatives	Criteria								
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
DM_1	A_1	ML	MH	H	H	H	H	MH	H	M-H
	A_2	M	M	MH	M	L-ML	MH	M	MH	MH
	A_3	L	ML-M	VH	M	ML	MH	H	H	M
	A_4	MH	H	H	VH	H	H	MH-H	MH	H
DM_2	A_1	L-ML	M-MH	H	MH	H	MH-H	MH	MH	MH
	A_2	M	ML	M-H	M-MH	ML	H	ML	MH	M-MH
	A_3	VL	ML	H	M-MH	ML	H	VH	VH	ML
	A_4	H	MH	H	H	MH	H	MH	MH-H	MH
DM_3	A_1	ML	MH	H	H	H	H	MH	H	M
	A_2	M-MH	M-MH	M	M	M	MH-H	M	M-MH	M
	A_3	L	ML	VH	M	ML-M	MH	H	H	M
	A_4	H-VH	H	VH	H	H	MH	H	H	H
DM_4	A_1	ML	ML	MH	H	MH	MH	H	H	MH
	A_2	ML	ML	M	MH	H	H	ML	ML	M
	A_3	L-ML	L	H-VH	MH	M	MH-H	VH	VH	ML
	A_4	H	H-VH	MH	VH	H	MH	H	H	M-MH
DM_5	A_1	M	MH	H	MH	H	MH	MH	H	MH
	A_2	ML	M	M	MH	ML	H	ML	M	M
	A_3	L	ML-M	VH	ML	M	MH	VH	H-VH	M
	A_4	H	H	H-VH	H-VH	MH-H	H-VH	MH-H	MH	H

TABLE V
THE TOTAL-RELATION MATRIX T

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.156	0.191	0.204	0.244	0.259	0.165	0.104	0.204	0.341
C_2	0.334	0.186	0.296	0.298	0.348	0.226	0.164	0.258	0.417
C_3	0.220	0.185	0.182	0.278	0.276	0.178	0.134	0.222	0.379
C_4	0.402	0.347	0.432	0.290	0.435	0.330	0.237	0.432	0.497
C_5	0.348	0.333	0.350	0.244	0.264	0.264	0.173	0.340	0.424
C_6	0.306	0.259	0.329	0.341	0.376	0.185	0.219	0.368	0.398
C_7	0.193	0.199	0.281	0.258	0.305	0.228	0.109	0.320	0.324
C_8	0.325	0.342	0.421	0.381	0.419	0.263	0.191	0.263	0.453
C_9	0.219	0.213	0.233	0.257	0.284	0.177	0.142	0.263	0.228

TABLE VI
INFLUENCES AND WEIGHTS OF CRITERIA

Criteria	R	C	$R + C$	R - C	Weights
C_1	1.869	2.503	4.372	-0.634	0.096
C_2	2.528	2.255	4.783	0.273	0.105
C_3	2.054	2.728	4.782	-0.673	0.105
C_4	3.400	2.591	5.991	0.809	0.132
C_5	2.740	2.965	5.705	-0.225	0.125
C_6	2.779	2.017	4.796	0.762	0.106
C_7	2.218	1.473	3.692	0.745	0.082
C_8	3.058	2.670	5.729	0.388	0.125
C_9	2.017	3.462	5.479	-1.445	0.124

TABLE VII
THE UNCERTAIN LINGUISTIC COLLECTIVE DECISION MATRIX $\tilde{X}$

	A_1	A_2	A_3	A_4
C_1	[s2, s2]	[s2.8, s2.8]	[s1, s1]	[s5, s5]
C_2	[s3.8, s4]	[s2.8, s2.8]	[s2, s2.4]	[s5, s5]
C_3	[s5, s5]	[s3, s3.8]	[s5.8, s6]	[s5, s5.4]
C_4	[s4.8, s4.8]	[s3.4, s3.8]	[s3, s3.4]	[s5.4, s5.8]
C_5	[s5, s5]	[s2.4, s2.4]	[s2.4, s2.8]	[s4.8, s5]
C_6	[s4.4, s4.8]	[s4.8, s5]	[s4, s4.4]	[s4.8, s4.8]
C_7	[s4, s4]	[s2.4, s2.4]	[s5.8, s5.8]	[s4.4, s5]
C_8	[s5, s5]	[s3.4, s3.8]	[s5.4, s5.8]	[s4.4, s4.8]
C_9	[s3.8, s4.2]	[s3, s3.4]	[s2.8, s2.8]	[s4.8, s4.8]

TABLE VIII
THE NORMALIZED UNCERTAIN LINGUISTIC DECISION MATRIX $\tilde{R}$

	A_1	A_2	A_3	A_4
C_1	[s4, s4]	[s3.2, s3.2]	[s5, s5]	[s1, s1]
C_2	[s2, s2.2]	[s3.2, s3.2]	[s3.6, s4]	[s1, s1]
C_3	[s5, s5]	[s3, s3.8]	[s5.8, s6]	[s5, s5.4]
C_4	[s1.2, s1.2]	[s2.2, s2.6]	[s2.6, s3]	[s0.2, s0.6]
C_5	[s1, s1]	[s3.6, s3.6]	[s3.2, s3.6]	[s1, s1.2]
C_6	[s4.4, s4.8]	[s4.8, s5]	[s4, s4.4]	[s4.8, s4.8]
C_7	[s4, s4]	[s2.4, s2.4]	[s5.8, s5.8]	[s4.4, s5]
C_8	[s5, s5]	[s3.4, s3.8]	[s5.4, s5.8]	[s4.4, s4.8]
C_9	[s1.8, s2.2]	[s2.6, s3]	[s3.2, s3.2]	[s1.2, s1.2]

Note that the linguistic quantifier "most" is utilized in the information aggregation and the ULOWA weight vector is computed as $\omega = (0,\ 0.2,\ 0.4,\ 0.4,\ 0)^T$ by (17)-(18). Subsequently, the normalized uncertain linguistic decision matrix $\tilde{R} = \left[\tilde{r}_{ij}\right]_{4\times 8}$ is established via (26), as shown in Table VIII. Next, the ranking indices $\tilde{y}_i$, d_i and $\tilde{u}_i$ for the four alternatives are calculated by (27)-(30) and the final ranking is determined by referring to the dominance theory [49]. The results of the calculations are tabulated in Table IX. Therefore, it is concluded that the site in Baoshan district (A_3) is the most desirable one for the considered EVCS location problem.

C. Sensitive Analysis

In the above case study, the ULOWA weight vector $\omega = (0,\ 0.2,\ 0.4,\ 0.4,\ 0)^T$ based on the linguistic quantifier "most" is adopted in the information aggregation to diminish the influence of extreme evaluations provided by experts. In this part, a sensitive analysis by changing the weight vector

TABLE IX
RANKING RESULTS BY THE UL-MULTIMOORA METHOD

Alternatives	$\tilde{y}_i$	Ranking	d_i	Ranking	$\tilde{u}_i$	Ranking	Final ranking
A_1	$[s_{3.049}, s_{3.162}]$	3	1.468	3	$[s_{3.217}, s_{3.291}]$	3	3
A_2	$[s_{3.152}, s_{3.409}]$	2	1.477	2	$[s_{3.527}, s_{3.674}]$	2	2
A_3	$[s_{4.184}, s_{4.442}]$	1	1.129	1	$[s_{4.029}, s_{4.167}]$	1	1
A_4	$[s_{2.449}, s_{2.668}]$	4	1.558	4	$[s_{2.601}, s_{2.833}]$	4	4

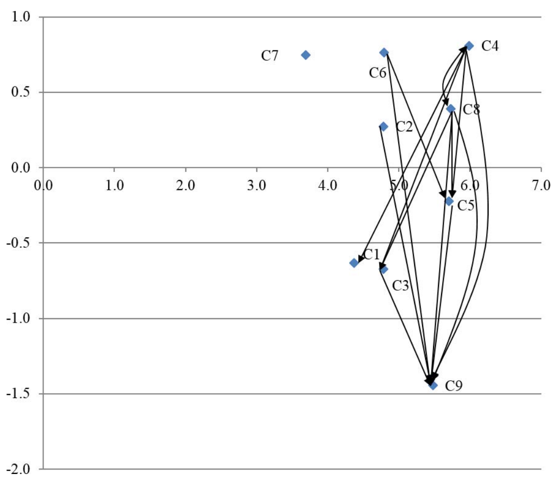

Fig. 4. Causal relation diagram for the case study.

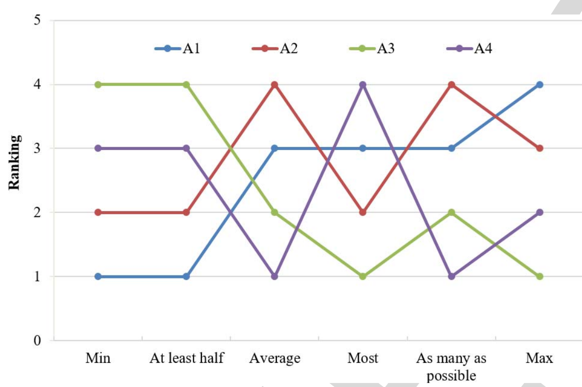

Fig. 5. Results of sensitivity analysis.

ω is carried out to measure the impact of biased assessment data on the ranking results yielded by the proposed approach. The considered cases include "minimum", "at least half", "average", "as many as possible" and "maximum" and their corresponding aggregation weight vectors are $\omega = (1, 0, 0, 0, 0)^T, \omega = (0.4, 0.4, 0.2, 0, 0)^T, \omega = (0.2, 0.2, 0.2, 0.2, 0.2)^T, \omega = (0, 0, 0.2, 0.4, 0.4)^T$, and $\omega = (0, 0, 0, 0, 1)^T$, respectively. Fig. 5 displays the results of the sensitivity analysis according to theses weight vectors.

From Fig. 5, we can find that the rankings of the four alternative sites are influenced greatly by the weight vector ω. For example, A_4 is the most suitable site for the EVCS site selection when "average" and "as many as possible" are used, while in terms of the linguistic quantifier "most", it is the lowest ranked location (i.e., the worst site) and A_3 becomes the best choice at the same time. Particularly, the influence of unfair assessments on the optimal EVCS site results can be evidently seen in the rank orderings derived in the cases of "minimum" and "maximum". They are quite different from the ranking determined by the linguistic quantifier "most", which can relieve the influence of unfair evaluations on the ranking results by assigning low weights to those "false" or "biased" ones. Therefore, utilizing the ULOWA operator in the proposed approach to deal with false or biased opinions is of great importance and benefit to the optima site selection of EVCSs in real-life situations.

D. Discussions

There are some important insights from the results produced by the proposed EVCS site selection approach. First, according to the UL-MULTIMOORA, the ranking of the four alternative sites is $A_3 \succ A_2 \succ A_1 \succ A_4$, which is in accordance with the one derived by the fuzzy TOPSIS method [8]. This indicates the effectiveness of the proposed approach. However, in comparison with other sitting methods, the proposed approach to locate EVCSs has the following advantages: (1) the ambiguity and diverse linguistic information of decision makers can be well handled and modeled using uncertain linguistic variables; (2) various types of correlations among evaluation criteria can be taken into account by the grey DEMATEL technique; (3) by using the modified MULTIMOORA approach, a more robust and credible ranking of alternative sites can be achieved as it summarizes three different methods. In addition, the ranking result of the EVCS sites obtained in this study are validated via getting feedback from the expert groups participated in this case study. According to the domain experts, the proposed hybrid MCDM approach is more suitable for the location problem of public charging stations and can help decision makers find the optimal site effectively.

Second, based on the obtained causal relation diagram Fig. 4, the interrelationships among the nine criteria can be determined. It can be found that the criteria with the highest prominence values are construction cost (C_4), annual operation and maintenance cost (C_5), and service capability (C_8), which are consistent with the criteria weights. That is, they are critical and well networked criteria and should be the focus of decision makers. Besides, the causal relation diagram determines that the criteria with the highest net cause values include construction cost (C_4), harmonization of EVCS with the development planning of urban road network and power grid (C_6) and traffic convenience (C_7). This shows that the three criteria should be improved first because they are the most prominent causal factors relative to other criteria. Moreover, an in-depth check of Fig. 4 shows that adverse impact on people's lives (C_9)

is a criterion being affected most; thus the adverse impact on people's lives is an important problem which needs more attention. All the evaluation criteria indicate the necessary behaviors to improve EVCS site selection for the considered problem. Therefore, each of the criteria should be evaluated for the EVCS site selection in accordance with the causal relation diagram.

VI. Conclusions

EVCSs play a pivotal role in the successful development of EVs and the optimal location of public charging facilities has received much attention in recent years. In this paper, we present an integrated MCDM approach based on grey DEMATEL and UL-MULTIMOORA to select the most suitable site for locating EV charging facilities. The proposed approach can not only effectively tackle ambiguity and diverse linguistic assessments of decision makers with uncertain linguistic variables, but also allows us to create a causal relation diagram for analyzing complex interactions among criteria with the grey DEMATEL. Moreover, we can determine the reasonable and credible ranking of candidate locations and identify the best one for locating an EVCS based on the UL-MULTIMOORA method.

An empirical example is presented to demonstrate the effectiveness of the proposed EVCS site selection approach. The result implies that the evaluation criteria are proved having interrelations and self-feedback relationships. Though the influence of all criteria have to be considered in the EVCS site selection process, domain experts have noted that economy related criteria should be given the top priority with bigger weights. By using the UL-MULTIMOORA method, the alternative located in the Baoshan district is found to be the optimal site for the considered problem. Moreover, a comparative analysis with the existing method is performed to examine the validity and superiority of the developed approach. It has been shown that the integrated MCDM framework proposed in this paper provides a practical and adequate tool to address the multifaceted EVCS site location problems with interdependent criteria.

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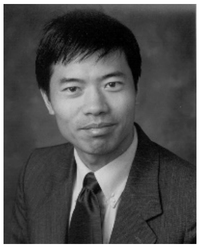

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