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A New Decision-Making Framework for Site Selection of Electric Vehicle Charging Station with Heterogeneous Information and Multi-Granular Linguistic Terms

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***Abstract*—As a key technology to perform sustainable development in transportation, electric vehicles have been largely welcomed due to their advantages in energy savings and low carbon emission. The main step in promoting these vehicles is the selection of the appropriate electric vehicle charging station (EVCS) site. EVCS site selection is a laborious task because it involves a series of conflicting quantitative and qualitative criteria from several dimensions. The quantitative criteria are usually expressed by numerical data, while qualitative criteria are commonly represented by linguistic terms. Furthermore, the linguistic terms generated by different decision makers are usually defined on multi-granular linguistic term sets. In this paper, we present a new decision-making framework to select sustainable EVCS sites within the context of heterogeneous information and multi-granular linguistic terms. First, three information transformation mechanisms are defined to unify the heterogeneous information and multi-granular linguistic terms into interval-valued belief structures. Afterwards, shadowed sets theory is utilized to reflect the personalized individual semantics of linguistic terms. Then, with the aid of the evidential reasoning algorithm, a new information fusion method is proposed to generate the interval-valued expected utilities of alternatives. Subsequently, an improved minimax regret approach is developed to compare and rank the interval-valued expected utilities. The proposed decision-making framework is then implemented to solve a case study for EVCS site selection. Further analysis and comparisons with other methods are also conducted to show the applicability and feasibility of the current proposal.**

***Index Terms*—Electric vehicle charging station, evidential reasoning algorithm, heterogeneous information, information transformation mechanisms, interval-valued ranking approach.**

I. INTRODUCTION

THE acceleration of urbanization, the development of the economy, and the growth of population are usually accompanied by excessive consumption of energy [1]. The energy demand is expected to increase with an average growth rate of 1.8% per year until 2023 [2]. According to the data published by the international energy agency, fossil fuels are still the main supplier of energy, which occupies 81% of the total global energy consumption in 2019 [3]. However, the overutilization of fossil fuels poses two major challenges. The first is the energy crisis. Fossils are finite and non-renewable, which means that they may be run out in the foreseeable future [4]. Another is environmental pollution. The combustion of fossil fuels will release a lot of carbon dioxide, which will exacerbate the greenhouse effect [5]. Therefore, it is essential to explore clean and sustainable alternatives. As a foremost determination of energy demand [6], the transport industry has taken some actions to reduce the consumption of fossil fuels, for example, exploring clean means of transportation to replace fossil fuel-based vehicles.

The electric vehicle is driven by an electric motor and a rechargeable battery, which is low in emissions, low in cost, and high in efficiency [7]. Meanwhile, if an appropriate charging mode is adopted, the electric vehicle can shift the peak power load, provide a spin reserve and improve the penetration of renewable energy power [8]. So, the development of electric vehicles can address concerns related to the depletion of fossil resources and promote the safe, stable and economical operation of the power grid [9]. In recent times, a growing number of countries have implemented different strategies to promote the production and sales of electric vehicles. According to the statistics, the deployment of electric vehicles has been growing rapidly over the past ten years, with 10 million units on the world's roads at the end of 2020. Moreover, despite the influence of the COVID-19 epidemic, the registration of electric vehicle companies increased by 41% in 2020 [3]. The rapid growth of electric vehicles brings a huge demand for electric vehicle charging stations (EVCSs).

As the energy provider of electric vehicles, the EVCS is the foundation for the development of the electric vehicle industry. Building efficient, convenient, and economical EVCS can not only improve consumers' willingness to buy but also promote the development of the vehicle industry. There are mainly three types of EVCSs, namely, conductive charging station, inductive charging station, and battery replacement station [10]. Among them, the conductive charging station is much cheaper and more efficient, so it is the most widely installed charging station [11]. Based on this, this paper focuses on studying the conductive charging station. The foremost and critical step in installing EVCS is to select a sustainable site [12], which is beneficial to improve the service quality and operational efficiency of EVCS. Therefore, it is essential to utilize proper methods to determine the optimal site for EVCS.

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In practice, the EVCS site selection is usually influenced by multiple conflicting criteria from several dimensions, e.g., society, economy, and environment [9], [13]. In general, these criteria can be classified into two categories, i.e., quantitative criteria and qualitative criteria. The modeling of the evaluation information under these two categories of criteria is usually different [14]–[16], i.e., the evaluation values are characterized by heterogeneous information formats. Specifically, the quantitative criteria are usually expressed by the numerical data, while the qualitative criteria are often represented by the linguistic terms [17]–[19]. Moreover, due to the different experiences and knowledge of humans, the linguistic terms elicited by different decision makers are usually defined on multi-granular linguistic term sets [20], [21]. How to deal with the heterogeneous information and multi-granular linguistic terms is still an open problem.

In this paper, a new decision-making framework is proposed to tackle the EVCS site selection problems within the context of heterogeneous information and multi-granular linguistic terms. The proposed decision-making framework mainly consists of three stages, i.e., information unification, information fusion, and alternative ranking. First, three information transformation mechanisms are proposed to transform the heterogeneous information and multi-granular linguistic terms into interval-valued belief structures distributed on a set of general assessment grades. In the proposed transformation mechanisms, the shadowed sets [22], [23] are used to model the fuzzy assessment grade to reflect the personalized individual semantics of the linguistic terms. Then, the evidential reasoning (ER) algorithm [24] is extended to fuse the interval-valued belief structures and to generate the interval-valued expected utilities of alternatives. Finally, an improved minimax regret (IMR) approach is introduced to compare and rank the interval-valued expected utilities.

The main contributions of this paper are summarized below.

(1) This paper allows experts to express/elicit the evaluation information by using heterogeneous information and multi-granular linguistic terms, and establishes three information transformation mechanisms to achieve the transformation from the heterogeneous and multi-granular linguistic terms information to the interval-valued belief structures, which not only provide more flexibility to reflect the difference of criteria and decision-makers but also preserve the maximum information elicited by decision-makers.

(2) Shadowed sets are introduced to reflect the personalized individual semantics of the linguistic terms. Unlike most of the existing studies about shadowed sets, this paper assumes the membership degree of the object in the shadowed area is a variable instead of a crisp value. In this way, the excellent performance of the shadowed sets in uncertain information processing can be better preserved.

(3) The ER algorithm is extended to fuse the evaluation information and generate the interval-valued expected utilities of alternatives. To compare and rank these obtained interval-valued expected utilities, a new interval-valued ranking approach is developed. The proposed approach can effectively overcome the shortcomings of existing interval-valued ranking approaches (see Subsection IV-C) and produce more reasonable and reliable results.

The paper is organized as follows. Section II reviews the literature related to EVCS site selection. In Section III, some basic concepts about shadowed sets, computing with words and ER algorithm are reviewed. In Section IV, three information transformation mechanisms, an ER algorithm-based information fusion method and a new interval-valued ranking approach are provided. Section V introduces the procedure of the proposed decision-making framework. In Section VI, a case study is provided about the selection of the EVCS site. Conclusions and some future perspectives are included in Section VII.

II. Literature Review

A suitable EVCS site not only contributes to the sustainable development of the city but also benefits relevant stakeholders. To select the best EVCS site, many studies have been conducted from a mathematical optimization perspective. For example, Liu et al. [25] constructed a mathematical optimization model with the objective function of minimizing the total costs to select the optimal EVCS site. Shahraki et al. [26] constructed a mathematical optimization model to determine the best location of EVCS from the perspective of maximizing the amount of distance traveled being electrified. Taking into account the uncertainties associated with load values and electricity market price, Shojaabadi et al. [27] presented a mathematical optimization model to determine the optimal EVCS site. Boujelben and Gicquel [28] constructed a mixed integer linear programming (MINLP) model to select the optimal EVCS location under driving range uncertainty. Kadri et al. [29] developed a multi-stage stochastic integer programming model to optimize EVCS location to maximize the expected value of the satisfied recharging demand. Zhou et al. [30] established a bi-level programming model to select the optimal EVCS site with the consideration of uncertain charging demands. Kabli et al. [31] proposed a two-stage stochastic programming model to determine the optimal EVCS location. To select the optimal EVCS site in remote communities, Shaaban et al. [32] constructed a multi-objective MINLP model to minimize two conflicting indicators: 1) deployment and operation costs and 2) associated greenhouse gas emissions. Bai et al. [33] formulated the EVCS site selection problem as a bi-objective mixed-integer mathematical model with two objectives of minimizing cost and maximizing service quality. These studies provide feasible solutions for EVCS site selection from the perspective of quantitative optimization. However, the EVCS site selection involves not only quantitative criteria but also qualitative criteria, so it is necessary to consider both qualitative and quantitative information to determine the optimal EVCS site.

The multi-criteria decision-making (MCDM) methods provide us with an effective way to balance these criteria and generate rational results. Therefore, many studies have focused on the use of MCDM methods to solve the EVCS site selection problems. For example, Guo and Zhao [8] introduced the fuzzy TOPSIS method to select the optimal EVCS site from a sustainability perspective. Cui et al. [34] proposed a Pythagorean fuzzy VIKOR method to determine the best EVCS site in uncertainty environments. Erbaş et al. [35] developed a fuzzy MCDM method based on a geographic information system to solve the EVCS site selection problems. By combining the linguistic entropy weight model and fuzzy axiomatic design, Feng et al. [36] presented an integrated MCDM method to select a suitable site for EVCS. In [37], by combing AHP, PROMETHEE, and VIKOR, an integrated MCDM method is developed to select the optimal EVCS site. Guler and Yomralioglu [38] proposed an integrated MCDM method by combining fuzzy AHP and TOPSIS to determine the most suitable EVCS site under uncertain environments. Ju et al. [39] divided the criteria into four categories and presented a gray relational projection method to balance these criteria and determine the optimal EVCS site. Karaşan [40] developed an intuitionistic fuzzy MCDM method to solve the EVCS site selection problems. To model the uncertainty of EVCS site selection, Liang et al. [41] proposed a gained and lost dominance score II method. In [42], an evaluation criteria system including 3 main criteria and 18 sub-criteria is established and a three-phase fuzzy MCDM method is provided to determine the optimal EVCS site. Rani and Mishra [12] developed a Fermatean fuzzy Einstein aggregation operators-based MULTIMOORA method to solve the EVCS site selection problems in uncertain environments. In [43], a three-step MCDM method is developed to determine the optimal EVCS site for Istanbul, Turkey. Ahmad et al. [44] conducted a systematic review of EVCS selection from the perspectives of optimization techniques, objective functions, constraints, EV load modeling, vehicle-to-grid strategy, and integration of distributed generation and charging types. Table I summarizes the representative studies that have used MCDM methods for EVCS site selection.

TABLE I
STUDIES ON EVCS SITE SELECTION

Solution methodology	References
Fuzzy TOPSIS method	[8], [43], [45]
Fuzzy VIKOR method	[34], [46]
Information system-based fuzzy MCDM method	[35], [47], [48], [49], [50]
Gained and lost dominance score II method	[41]
Fuzzy grey relation analysis-based model	[13], [39], [42]
MULTIMOORA method	[12]
PROMETHEE method	[51]
Integrated MCDM method	[36], [37], [38], [40], [52], [53]

Despite the significant contributions that have been made, there are still several compelling challenges and research gaps to be tackled.

(1) Most of the existing studies on EVCS site selection assume that evaluation information under different criteria is expressed by homogeneous information formats. However, due to the different characteristics of the criteria, the evaluation information under them usually should be expressed by heterogeneous information formats.

(2) The encoding of linguistic terms plays a vital role in computing with words. In practice, the same linguistic term can mean different things to different people [54]. However, most of the existing studies on EVCS site selection encode linguistic terms by crisp values or type-1 fuzzy sets, which does not reflect the personalized individual semantics of linguistic terms.

(3) In most of the existing studies, the decision-makers are asked to provide their opinions on the same linguistic scale. However, different decision-makers may have different knowledge and backgrounds, which implies that the linguistic terms elicited by them may be defined on multi-granular linguistic term sets.

Because of these challenges and research gaps, this paper proposes a novel decision-making framework for EVCS site selection. The proposed decision-making framework contributes to EVCS site selection according to the following aspects. First, the heterogeneous information and multi-granular linguistic terms are utilized to express the evaluation information of EVCS site selection. Such a preference structure can effectively reflect the different characteristics of criteria and decision-makers. Second, the shadowed sets are introduced to construct the multi-granular linguistic terms, which contribute to describing the personalized individual semantics of linguistic terms. Moreover, some information transformation mechanisms are established to transform the heterogeneous information and multi-granular linguistic terms into unified interval-valued belief structures and then the ER algorithm is extended to fuse the interval-valued belief structures and generate the interval-valued expected utilities, which lays a good foundation to manage heterogeneous information and multi-granular linguistic terms involved in EVCS site selection. Finally, an improved minimax regret (IMR) approach is proposed to compare and rank the interval-valued expected utilities. The proposed approach can effectively overcome the limitations of the existing interval-valued ranking approaches (see Section IV-C) and provide reliable ranking results.

III. Preliminaries

This section introduces some basic concepts of shadowed sets, computing with words, and ER algorithm.

A. Shadowed sets

The shadowed sets, initially proposed by Pedrycz [22], [23], can be considered as the three-valued approximation of fuzzy sets. Formally, for a nonempty universal set U, a shadowed set A can be defined by a set-valued mapping coming in the following form:

$$A : U \to \{0, [0, 1], 1\} \tag{1}$$

For $x \in U$, if its mapping value is equal to 1, it is fully compatible with the concept conveyed by shadowed sets. All such elements constitute the core area of the shadowed sets and are expressed as:

$$core(A) = \{x \in U | \mu_A(x) = 1\} \tag{2}$$

where $\mu_A(x)$ denotes the membership degree of an element x belonging to the shadowed set A.

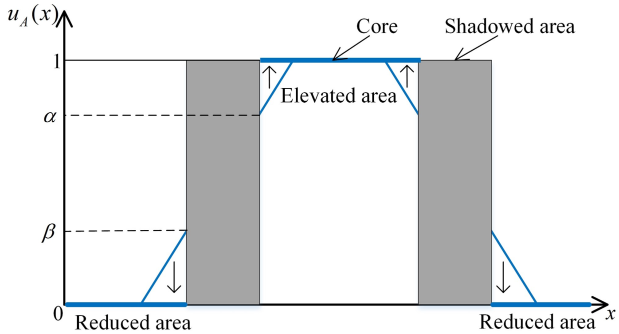

Fig. 1. The construction of the shadowed set

If the mapping value of element x is characterized by the unit interval [0, 1], it is deemed as uncertainty. Such elements form the shadowed area of the shadowed set A, which can be denoted as:

$$sh(A) = \{x \in U | \mu_A(x) = [0, 1]\} \tag{3}$$

The element whose mapping value is equal to 0 is excluded from the shadowed set A.

According to the quantitative three-valued approximation, the shadowed set can also be expressed as [55]:

$$\mu_A(x) = \begin{cases} 0, \mu_A(x) \leq \beta \\ 1, \mu_A(x) \geq \alpha \\ [0,1], \beta < \mu_A(x) < \alpha \end{cases} \tag{4}$$

where β and α are two predefined thresholds used in constructing a shadowed set, which satisfy $0 \leq \beta \leq \alpha \leq 1$.

In the construction process, if the membership degree of the element is larger than threshold α, we elevate its membership degree to 1; if the element's membership degree is smaller than threshold β, we reduce the membership degree to 0; if the membership degree of the element is between β and α, its membership degree is mapped into the unit interval [0, 1]. The Fig.1 is provided to visualize the construction process.

The values of the thresholds β and α can be calculated by minimizing the following objective function [22], [56].

$$\begin{aligned} V_{(\alpha,\beta)}(\mu_A) =& Reduced \quad area_{(\alpha,\beta)}(\mu_A) + Elevated \\ & area_{(\alpha,\beta)}(\mu_A) - Shadowed \quad area_{(\alpha,\beta)}(\mu_A) \\ =& \sum_{x_i \in U, \mu_A(x_i) \leq \beta} \mu_A(x_i) \\ &+ \sum_{x_i \in U, \mu_A(x_i) \geq \alpha} (1 - \mu_A(x_i)) \\ &- Card(x_i \in U | \alpha < \mu_A(x_i) < \beta) \end{aligned} \tag{5}$$

B. Computing with words based on shadowed sets

In general, words means different things to different people [54]. How to reflect this difference is a hot-topic in academic research. In this subsection, we aim to tackle this issue by encoding the linguistic terms into shadowed sets. Using the shadowed sets to construct the linguistic terms consists of four phases [56], [57], which are briefly described as follows.

Phase 1. Data collection. Wu et al. [58] collected the survey data about linguistic terms by questionnaire survey. One item to be mentioned is that the survey data is modelled by interval values in the domain [0, 10]. In this paper, we, respectively, investigate the five linguistic terms and seven linguistic terms by the questionnaire survey: what range do you think the linguistic term should belong to (from 0 to 10)? Suppose that there are N survey data $\{[l_k, r_k]\}_{k=1}^{N}$ for one linguistic term.

Phase 2. Data pre-processing. In [58], [59], an effective data processing approach is provided to eliminate unreasonable interval values. The approach includes four main steps: bad data processing, outlier processing, tolerance limit processing, and reasonable-interval processing.

Step 1. Bad data processing. In the survey process, some interviews may provide invalid or unreasonable answers, which fall outside the domain [0, 10]. The interval values that do not meet the following conditions will be rejected.

$$0 \leq l_k \leq r_k \leq 10; r_k - l_k < 10 \tag{6}$$

After this step, there are $N\prime$ interval values left.

Step 2. Outlier processing. This step aims to eliminate the outliers. In this step, the Box and Whisker tests will be respectively performed on l_k, r_k and $v_k = r_k - l_k$. Only the interval values satisfying the following equations will be kept.

$$l_k \in [Q_l(0.25) - 1.5I_l, Q_l(0.75) + 1.5I_l] \tag{7}$$

$$r_k \in [Q_r(0.25) - 1.5I_l, Q_r(0.75) + 1.5I_r] \tag{8}$$

$$v_k \in [Q_v(0.25) - 1.5I_v, Q_v(0.75) + 1.5I_v] \tag{9}$$

where Q_l, Q_r and Q_v respectively denote the quartiles of the left-end points, right-end points, and interval lengths, whilst I_l, I_r and I_v respectively represent the interquartile ranges of the left-end points, right-end points and interval lengths.

This step reduces $N\prime$ interval values to $N\prime\prime$ interval values.

Step 3. Tolerance limit processing. To compute the mean and standard deviation more accurately, the interval values that do not satisfy the following conditions will be rejected.

$$l_k \in [m_l - \eta\sigma_l, m_l + \eta\sigma_l] \tag{10}$$

$$r_k \in [m_r - \eta\sigma_r, m_r + \eta\sigma_r] \tag{11}$$

$$v_k \in [m_v - \eta\sigma_v, m_v + \eta\sigma_v] \tag{12}$$

where m_l, m_r and m_v are respectively the means of left-end points, right-end points and interval lengths, and σ_l, σ_r and σ_v denote the standard deviations of left-end points, right-end points and interval lengths; η is the tolerance factor, which can be obtained based on the sample size and the confidence level.

After this step, $N\prime\prime\prime$ interval values will remain.

Step 4. Reasonable interval processing. This step is used to eliminate the interval values that do not overlap with others. The interval values that do not satisfy the following equation will be rejected.

$$2m_l - \zeta^* \leq l_k < \zeta^* < r_k \leq 2m_r - \zeta^* \tag{13}$$

where

$$\zeta^* = \frac{(m_r\sigma_l^2 - m_l\sigma_r^2) \pm \sigma_l\sigma_r[(m_l - m_r)^2 + 2(\sigma_l^2 - \sigma_r^2)\ln(\sigma_l/\sigma_r)]^{\frac{1}{2}}}{\sigma_l^2 - \sigma_r^2} \tag{14}$$

In which, $\pm$ is selected by testing whether it satisfies $m_l \leq \zeta^* \leq m_r$ [59].

This step reduces $N\prime\prime\prime$ interval values to $M\prime$ interval values.

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Phase 3. Representative intervals calculation. The distributions of the end-points of interval values can reflect the different cognitions of people on the same linguistic term [56]. Thus, we can calculate the representative intervals for the end-points to reflect such differences on the linguistic term. In [56], based on the linear interpolation model [60], a percentile method is provided to realize this objective.

The representative intervals of the left end-points can be calculated by:

$$T_q^L = l_{\lfloor M\prime * q\rfloor} + rem(M\prime * q, 1)(l_{\lfloor M\prime * q+1\rfloor} - l_{\lfloor M\prime * q\rfloor}) \quad (15)$$

$$T_{1-q}^L = l_{\lfloor M\prime *(1-q)\rfloor} + rem(M\prime *(1-q), 1)(l_{\lfloor M\prime *(1-q)+1\rfloor} - l_{\lfloor M\prime *(1-q)\rfloor}) \quad (16)$$

$$l_k \leq l_{k+1}, k = 1, \cdots, M\prime \quad (17)$$

in which T_q^L and $T_{(1-q)}^L$ respectively denote the $100qth$ and $100(1-q)th$ percentiles of the left end-points, $q(q<0.5)$ is a predefined value, $\lfloor \cdot \rfloor$ is the floor function used to calculate the integral part of the corresponding value and $rem(\bullet, 1)$ employs the mod function to calculate the remainder of the corresponding value.

Similarly, we can calculate the $100qth$ and $100(1-q)$ percentiles of the right end-points as T_q^R and T_{1-q}^R.

Thus, the left and right representative intervals can be denoted as:

$$[LL, LR] = [T_q^L, T_{1-q}^L]; [RL, RR] = [T_q^R, T_{1-q}^R] \quad (18)$$

Phase 4. Linguistic term construction. After obtaining the representative intervals, the shape and parameters of the shadowed sets can be accordingly determined. Of note, the different relationships between the left and right representative intervals will lead to four types of shadowed sets, i.e., standard shadowed sets, left-shoulder shadowed sets, right-shoulder shadowed sets, and non-cored shadowed sets [56]. This paper only focuses on the standard shadowed sets, which can be expressed as $A = A(\text{“}S\text{”}, LL, LR, RL, RR)$.

C. The evidential reasoning algorithm

The ER algorithm, which is based on Dempster–Shafer theory of evidence [61], can effectively model fuzzy and incomplete information by introducing a distributed modeling framework. To facilitate understanding, several primary concepts are briefly reviewed in this subsection.

Let $\Theta = \{\theta_1, \ldots, \theta_N\}$ be a family of exhaustive and exclusive hypotheses, which constitutes the frame of discernment. The power set of the frame of discernment consists of 2^N subsets and is expressed as follows [62], [63]:

$$2^\Theta = \{\emptyset, \{\theta_1\}, \ldots, \{\theta_N\}, \{\theta_1, \theta_2\}, \ldots, \{\theta_1, \theta_N\}, \{\theta_1, \ldots, \theta_{N-1}\}, \Theta\} \quad (19)$$

If the mapping function $m : 2^\Theta \to [0, 1]$ satisfies the following equations [62], [64]:

$$m(\emptyset) = 0; \sum_{\theta \subseteq \Theta} m(\theta) = 1 \quad (20)$$

then $m(\cdot)$ is called the basic probability assignment (BPA) function of θ. If $m(\theta_i) > 0$, θ_i is called the focal element.

For two BPA functions m_1 and m_2, the Dempster's combination rule is defined as follows [61]:

$$[m_1 + m_2](\theta) = \begin{cases} 0 & \theta = \emptyset \\ \frac{1}{1-\rho} \cdot \sum_{B \cap C = \theta} m_1(B) m_2(C) & \theta \neq \emptyset \end{cases} \quad (21)$$

where ρ denotes the conflict between two evidences and can be calculated as $\rho = \sum_{B \cap C = \emptyset} m_1(B) m_2(c)$.

Dempster's combination rule is demonstrated as an effective algorithm to fuse deterministic evidence. However, when evidences are characterized by interval probability masses (interval-valued belief structures), Dempster's combination rule will be invalid. For this reason, Wang et al. [63] proposed two equivalent algorithms: the ER recursive algorithm and the ER analytical algorithm. Here, we briefly introduce the ER analytical algorithm.

Suppose that there are L independent evidences $e_1, e_2, \cdots, e_L$, the BPA function of evidence e_i supporting θ_n is denoted as $m_{\theta_n,i}$. The integrated belief degree of the L independent evidences can be generated by the following pair of nonlinear optimization models [63]:

$$\max/\min \quad \zeta_{\theta_n}(e) = m_{\theta_n}/1 - \bar{m}_{P(\theta_n)} \quad (22)$$

$$s.t. m_{\theta_n} = \rho \cdot [\prod_{i=1}^{L} (m_{\theta_n}, i + \bar{m}_{P(\Theta),i} + \tilde{m}_{P(\Theta),i}) - \prod_{i=1}^{L} (\bar{m}_{P(\Theta),i} + \tilde{m}_{P(\Theta),i})], n = 1, \ldots, N \quad (23)$$

$$\tilde{m}_{P(\theta_n)} = \rho \cdot [\prod_{i=1}^{L} (\bar{m}_{P(\Theta),i} + \tilde{m}_{P(\Theta),i}) - \prod_{i=1}^{L} \tilde{m}_{P(\Theta),i}] \quad (24)$$

$$\bar{m}_{P(\theta_n)} = \rho \cdot [\prod_{i=1}^{L} \bar{m}_{P(\Theta),i}] \quad (25)$$

$$\rho = \{[\sum_{n=1}^{N} \prod_{i=1}^{L} (m_{\theta_n,i} + \bar{m}_{P(\Theta),i} + \tilde{m}_{P(\Theta),i}) - (N-1) \cdot \prod_{i=1}^{L} (\bar{m}_{P(\Theta),i} + \tilde{m}_{P(\Theta),i})]^{-1}\} \quad (26)$$

$$m_{\theta_n,i} = m_i(\theta_n) \in [m_{\theta_n,i}^-, m_{\theta_n,i}^+] = [w_i \cdot \xi_{\theta_n}^-(e_i), w_i \cdot \xi_{\theta_n}^+(e_i)] \quad (27)$$

$$\bar{m}_{P(\Theta),i} = \bar{m}_i(P(\Theta)) = 1 - w_i, i = 1, \ldots, L \quad (28)$$

$$\tilde{m}_{P(\Theta),i} = \tilde{m}_i(P(\Theta)) \in [\tilde{m}_{P(\Theta),i}^-, \tilde{m}_{P(\Theta),i}^+] = [w_i \cdot \xi_{P(\Theta)}^-(e_i), w_i \cdot \xi_{P(\Theta)}^+(e_i)] \quad (29)$$

$$\xi_{P(\Theta)}^-(e_i) = \max(0, 1 - \sum_{n=1}^{N} \xi_{\theta_n}^+(e_i)) \quad (30)$$

$$\xi_{P(\Theta)}^+(e_i) = 1 - \sum_{n=1}^{N} \xi_{\theta_n}^-(e_i) \quad (31)$$

$$\sum_{n=1}^{N} m_{\theta_n,i} + \bar{m}_{P(\Theta),i} + \tilde{m}_{P(\Theta),i} = 1, i = 1, \ldots, L \quad (32)$$

where $P(\Theta)$ denotes the power set of the frame of discernment Θ; $m_{\theta_n,i}$, $\bar{m}_{P(\Theta),i}$ and $\tilde{m}_{P(\Theta),i}$ are the BPA functions of evidence e_i; $\xi_{\theta_n}(e_i) = [\xi_{\theta_n}^-(e_i), \xi_{\theta_n}^+(e_i)]$ is the interval-valued belief degree of evidence e_i assigned to hypothesis θ_n.

IV. Managing Heterogeneous Information And Multi-Granular Linguistic Terms

This section aims to manage the heterogeneous information and multi-granular linguistic terms with the aid of distributed assessment structure. In subsection IV-A, three information transformation mechanisms are established to transform the heterogeneous information formats into interval-valued belief

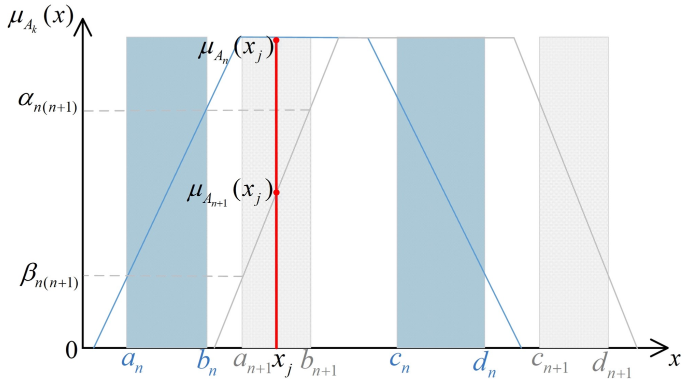

Fig. 2. The relations between crisp numbers and assessment grades

structures. In subsection IV-B, a pair of nonlinear programming models are constructed to fuse the interval-valued belief structures to generate the aggregated interval-valued belief structures. After obtaining the aggregated interval-value belief structures, some rules are proposed to calculate the interval-valued expected utility of each alternative. In subsection IV-C, considering the interval values cannot be directly compared and ranked, it is proposed an IMR approach to distinguish them and output the decision results.

A. Information transformation mechanisms

In practice, the evaluation information under different kinds of criteria is usually expressed in different forms. To be specific, the quantitative criteria are usually expressed by numerical data while the qualitative criteria are commonly represented by linguistic terms. Crisp values and interval values are the two most common and accessible types of numerical data. Hence, this paper focuses on utilizing crisp values, interval values, and linguistic terms to express the evaluation information. In this subsection, three information transformation mechanisms are established to conduct the heterogeneous information formats into the interval-valued belief structures distributed on a unified set of assessment grades.

1) Conducting crisp values into interval-valued belief structures: To realize the transformation between crisp values and belief structures, Yang et al. [62] modeled the assessment grades by the triangular fuzzy sets and developed a normalization technology to transform crisp values into precise belief structures. However, with the increasingly complex environment, the precise belief structures may fail to reflect the real situations [62], [65]. To tackle this limitation, we model the assessment grades by the shadowed sets and establish a new transformation mechanism to transform the crisp values into interval-valued belief structures based on the relative positional relations between crisp values and assessment grades. The Fig.2 reveals the relative positional relations between the crisp values and assessment grades.

Suppose that there is a set of general fuzzy assessment grades $\Omega = \{H_1, \ldots, H_N\}$. Without loss of generality, we suppose that a crisp value x_j belongs to two adjacent assessment grades H_n and H_{n+1} derived from the set of general fuzzy assessment grades with membership degrees $\mu_{A_n}(x_j)$ and $\mu_{A_{n+1}}(x_j)$, respectively. It seems logical that the crisp value can be equivalently characterized by the two adjacent assessment grade H_n and H_{n+1}. One way to achieve this goal is to normalize the membership degrees of the crisp value belonging to the two adjacent assessment grades. Because the assessment grade H_k are encoded by the shadowed set $A_k = A_k(\text{“}S\text{”}, a_k, b_k, c_k, d_k)$, $k = 1, \ldots, N$, we need to analyze the relationships between the crisp values and the shadowed sets. As discussed in subsection III-A, the shadowed sets consist of two parts: the core area and the shadowed area. Wherein, the membership degree of the core area is certain (equal to 1), so we only discuss the membership degree in the shadowed area. From Fig.2, we can conclude that when the crisp value distributed in the shadowed area, its membership degree may be any value between β_k and α_k, $k = 1, \ldots, N$ [39]. Based on the membership degrees, the interval-valued belief degrees of the crisp value x_j belonging to the assessment grades H_n and H_{n+1} can be generated by the following rules:

$$\xi^-(x_j \in H_n) = \frac{\mu_{A_n}(x_j)}{\mu_{A_n}(x_j) + \mu_{A_{n+1}}(x)} = \frac{1}{1+\alpha_{n+1}} \quad (33)$$

$$\xi^+(x_j \in H_n) = \frac{\mu_{A_n}(x_j)}{\mu_{A_n}(x_j) + \mu_{A_{n+1}}(x_j)} = \frac{1}{1+\beta_{n+1}} \quad (34)$$

$$\xi^-(x_j \in H_{n+1}) = \frac{\mu_{A_{n+1}}(x_j)}{\mu_{A_n}(x_j) + \mu_{A_{n+1}}(x_j)} = \frac{\beta_{n+1}}{1+\alpha_{n+1}} \quad (35)$$

$$\xi^+(x_j \in H_{n+1}) = \frac{\mu_{A_{n+1}}(x_j)}{\mu_{A_n}(x_j) + \mu_{A_{n+1}}(x_j)} = \frac{\alpha_{n+1}}{1+\beta_{n+1}} \quad (36)$$

According to the Eqs.(33)-(36), the crisp value x_j can be equivalently represented by the following interval-valued belief structure: $S(H_k(x_j)) = \{(H_n, [\xi^-(x_j \in H_n), \xi^+(x_j \in H_n)]), (H_{n+1}, [\xi^-(x_j \in H_{n+1}), \xi^+(x_j \in H_{n+1})])\}$.

Note 1: If the crisp value x_j only intersects the fuzzy assessment grade H_k and has no-empty intersection subset with any other assessment grades, then $\xi(x_j \in H_k) = [1, 1]$ can be directly obtained whether the crisp value is entirely included in H_k or not.

2) Conducting interval values into interval-valued belief structures: Due to the limitations of human thinking and the complexity of a realistic environment, it is difficult or even impossible for the decision makers to always express their opinions with crisp values. In this situation, the decision makers tend to employ some uncertain measurements to express their opinions. The interval values have been demonstrated as an effective tool to describe the uncertain information derived from the decision-makers [66]. Different from the crisp value, the interval value may span several assessment grades, thus its transformation is not as easy as the crisp value. In this subsection, we develop a new transformation mechanism to transform the interval values into interval-valued belief structures based on their relative positional relations.

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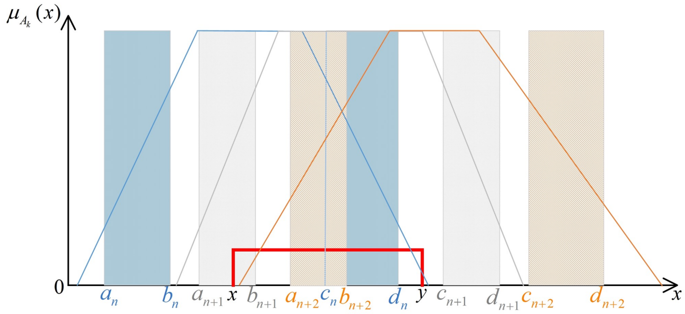

Fig. 3. The relative positional relations between interval value and fuzzy assessment grades

Let $[x, y]$ be an interval value, which intersects three adjacent assessment grades H_n, H_{n+1} and H_{n+2} derived from the set of general fuzzy assessment grades $\Omega = \{H_1, \ldots, H_N\}$ (see Fig.3). From Fig.3, we can obtain the typical relative positional relations between the interval value and the three adjacent assessment grades. The lengths of interval value [x, y] intersecting H_n, H_{n+1} and H_{n+2} can be denoted as l_n, l_{n+1} and l_{n+2}, respectively. Besides, we can conclude that the larger the length l_k is, the higher the belief degree of interval value $[x, y]$ belonging to H_k will be, $k = 1, \ldots, N$. To obtain the interval-valued belief degrees of the interval value $[x, y]$ assigning to the fuzzy assessment grade H_k, the following pair of nonlinear programming models are introduced:

$$\max/\min \quad \xi\left([x,y] \in H_k\right) = \frac{l_k(core) + \mu_{A_k}(x) \cdot l_k(shadow)}{\sum_{k=1}^{N}\left(l_k(core) + \mu_{A_k}(x) \cdot l_k(shadow)\right)} \tag{37}$$

$$s.t. \alpha_k \leq \mu_{A_k}(x) \leq \beta_k, k = 1, \ldots, N \tag{38}$$

$$l_n\left(core\right) = c_n - x \tag{39}$$

$$l_n\left(shadow\right) = d_n - c_n \tag{40}$$

$$l_{n+1}\left(core\right) = y - b_{n+1} \tag{41}$$

$$l_{n+1}\left(shadow\right) = b_{n+1} - x \tag{42}$$

$$l_{n+2}\left(core\right) = y - b_{n+2} \tag{43}$$

$$l_{n+2}\left(shadow\right) = b_{n+2} - a_{n+2} \tag{44}$$

where $l_k(core)$ is the length lied in the core area of the fuzzy assessment grade H_k; $l_k(shadow)$ is the length lied in the shadowed area and $\mu_{A_k}(x)$ is the membership function of assessment grade H_k, $k = 1, \ldots, N$.

Let $\xi^-([x, y] \in H_k)$ and $\xi^+([x, y] \in H_k)$ be the optimal objective function values of the above pair of nonlinear programming models, which respectively indicates the lower and upper belief degree of the interval value $[x, y]$ assessed to the assessment grade H_k, $k = 1, \ldots, N$. Thus, the interval value $[x, y]$ can be equivalently represented by the following interval-valued belief structure: $S(H_k([x, y])) = \{(H_k, [\xi^-([x, y] \in H_k), \xi^+([x, y] \in H_k)]), k = 1, \ldots, N\}$.

It is worth noting that not all interval-valued belief structures are valid. As pointed out by Wang et al. [63], the valid interval-valued belief structure must satisfy the condition $\sum_{k=1}^{N} \xi_k^- \leq 1$ and $\sum_{k=1}^{N} \xi_k^+ \geq 1$, where ξ_k^- and ξ_k^+ denotes the lower and upper bound of the interval-valued belief degree, respectively. Thus, we need to prove that the obtained interval-valued belief structures satisfy the condition $\sum_{k=1}^{N} \xi^-([x, y] \in H_k) \leq 1$ and $\sum_{k=1}^{N} \xi^+([x, y] \in H_k) \geq 1$.

Proof. See appendix A.

Note 2: If the interval value $[x, y]$ only intersects the fuzzy assessment grade H_k and has no-empty intersection subset with any other assessment grades, then $\xi([x, y] \in H_k) = [1, 1]$ can be directly obtained whether the interval value is entirely included in H_k or not, $k = 1, 2, \ldots, N$.

Remark 1: Since the survey data of linguistic terms are in the domain [0, 10], we need to normalize the crisp values and interval values according to the following rules.

Let $\{r_1, r_2, \cdots, r_n\}$ and $\{[r_1^-, r_1^+], [r_2^-, r_2^+], \cdots, [r_n^-, r_n^+]\}$ be the sets of crisp values and interval values, respectively. Then, the crisp values can be normalized by [67]:

$$x_j = \frac{r_j}{\max\limits_j\{r_j\}} \times 10 \tag{45}$$

The interval values can be normalized by [68]:

$$x = \frac{r_j^-}{\max\limits_j\{r_j^-, r_j^+\}} \times 10; y = \frac{r_j^+}{\max\limits_j\{r_j^-, r_j^+\}} \times 10 \tag{46}$$

3) Conducting linguistic terms into interval-valued belief structures: The decision-makers are more willing to provide their opinions by the linguistic terms in some situations. Moreover, the linguistic terms elicited by different decision makers are usually defined on multi-granular linguistic term sets. To computing with words, this subsection encodes the multi-granular linguistic terms into shadowed sets and proposes a new information transformation mechanism to transform the shadowed sets into interval-valued belief structures defined on a set of general assessment grades. Fig.4 is provided to show the relative positional relations between shadowed sets and fuzzy assessment grades.

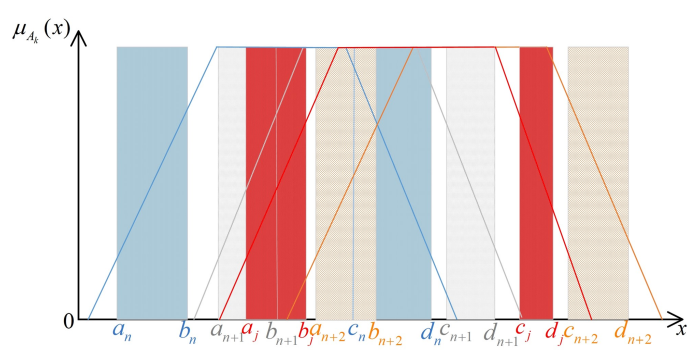

Fig. 4. The relative position relations between shadowed sets and fuzzy assessment grades

Suppose that a decision-maker provides his/her preference information by using linguistic terms with a certain linguistic granularity. To compute with words, the linguistic term is encoded into shadowed sets, denoted as $A_j = A_j(\text{"S"}, a_j, b_j, c_j, d_j)$. From Fig.4, we can observe that the shadowed set A_j intersects three adjacent assessment grades H_n, H_{n+1} and H_{n+2} derived from the set of general fuzzy assessment grades $\Omega = \{H_1, \ldots, H_N\}$ with the area of S_n, S_{n+1} and S_{n+2}, respectively. Besides, a large S_k implies a

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high belief degree of A_j belonging to H_k, $k = 1, \ldots, N$. Thus, it seems logical that the shadowed set A_j can be equivalently expressed by H_n, H_{n+1} and H_{n+2}.

The following pair of nonlinear programming models are introduced to normalize the area to generate the interval-valued belief degrees:

$$\max/\min \xi(A_j \in H_k) = S_k / \sum_{k=1}^{N} S_k \tag{47}$$

$$s.t.\alpha_k \le \mu_{A_k}(x) \le \beta_k, k = 1, \ldots, N \tag{48}$$

$$\alpha_j \le \mu_{A_j}(x) \le \beta_j \tag{49}$$

$$S_k = S_k(core) + \mu_{A_k}(x) S_k(shadow) + \mu_{A_j}(x) \tag{50}$$
$$S_j(shadow) + \min\{\mu_{A_k}(x), \mu_{A_j}(x)\} S_{k,j}(shadow)$$

$$S_n\,(core) = c_n - b_j \tag{51}$$

$$S_n\,(shadow) = d_n - c_n \tag{52}$$

$$S_{n+1}\,(core) = c_{n+1} - b_j \tag{53}$$

$$S_{n+1}\,(shadow) = d_{n+1} - c_{n+1} \tag{54}$$

$$S_{n+2}\,(core) = c_j - b_{n+2} \tag{55}$$

$$S_{n+2}\,(shadow) = b_{n+2} - a_{n+2} \tag{56}$$

$$S_j\,(shadow) = 2b_j - a_j - b_{n+1} + d_j - c_j \tag{57}$$

$$S_{n+1,j}\,(shadow) = b_{n+1} - a_j \tag{58}$$

where $\mu_{A_k}(x)$ and $\mu_{A_j}(x)$ denote the membership functions of $A_k = A_k(\text{“}S\text{”}, a_k, b_k, c_k, d_k)$ and $A_j = A_j(\text{“}S\text{”}, a_j, b_j, c_j, d_j)$, respectively.

Let $\xi^-(A_j \in H_k)$ and $\xi^+(A_j \in H_k)$ be the optimal objective function values of the above pair of nonlinear programming models. They respectively indicate the lower and upper belief degree of the shadowed set A_j assessed to the assessment grade H_k, $k = 1, \ldots, N$. Thus, the shadowed set A_j can be equivalently represented by the following interval-valued belief structure: $S(H_k(A_j)) = \{(H_k, [\xi^-(A_j \in H_k), \xi^+(A_j \in H_k)]), k = 1, \ldots, N\}$.

Now, it is necessary to prove that the obtained interval-valued belief structure is valid, that is, it meets the conditions: $\sum_{k=1}^{N} \xi^-(A_j \in H_k) \le 1$ and $\sum_{k=1}^{N} \xi^+(A_j \in H_k) \ge 1$.

Proof. See appendix A.

Note 3: If the shadowed set A_j only intersects the fuzzy assessment grade H_k and has no-empty intersection subset with any other assessment grades, then the shadowed set should completely belong to H_k and $\xi(A_j \in H_k) = [1, 1]$.

Remark 2: In this paper, we assume that the fuzzy assessment grades adopted in this paper have obvious differences. For example, for two fuzzy assessment grades H_n and H_{n+1}, although they are adjacent, their semantic difference is obvious, e.g., $H_n = \text{“}medium\text{”}$ and $H_{n+1} = \text{“}good\text{”}$. Thus, the situation in which the evaluation information (crisp values, interval values, and multi-granular linguistic terms) intersects with two or three adjacent fuzzy assessment grades derived from $\Omega = \{H_1, \ldots, H_N\}$ is sufficient to meet our requirements. However, we must point out that for more general situations in which the evaluation information intersects with more than three fuzzy assessment grades, the proposed transformation mechanisms are still effective and feasible. But this situation is not the focus of this paper, so we will not discuss it in detail for the time being.

B. The interval-valued ER algorithm for information fusion

This subsection extended the ER algorithm to fuse the interval-valued belief information under multiple criteria. In such an extended algorithm, both the belief structures and the criteria weights are expressed by interval values, which can provide more flexibility to reflect the subjective uncertainty. After fusing the interval-valued belief information, a pair of nonlinear optimization models are conducted to generate the interval-valued expected utility of each alternative.

1) The ER algorithm for fusing multiple interval-valued belief structures: This fusion process consists of two parts. The first one is transforming the interval-valued belief degrees into interval-valued BPAs by the following equations:

$$m_{k,l} = m_l(H_k) \in [m_{k,l}^-, m_{k,l}^+] = [w_l^- \cdot \xi_{k,l}^-(Z_i), w_l^+ \cdot \xi_{k,l}^+(Z_i)] \tag{59}$$

$$\bar{m}_{H,l} = \bar{m}_l(H) \in [\bar{m}_{H,l}^-, \bar{m}_{H,l}^+] = [1 - w_l^+, 1 - w_l^-] \tag{60}$$

$$\tilde{m}_{H,l} = \tilde{m}_l(H) \in [\tilde{m}_{H,l}^-, \tilde{m}_{H,l}^+] = [w_l^- \cdot \xi_{H,l}^-(Z_i), w_l^+ \cdot \xi_{H,l}^+(Z_i)] \tag{61}$$

$$\xi_{H,l}^-(Z_i) = \max(0, 1 - \sum_{k=1}^{N} \xi_{k,l}^+(Z_i)) \tag{62}$$

$$\xi_{H,l}^+(Z_i) = 1 - \sum_{k=1}^{N} \xi_{k,l}^-(Z_i) \tag{63}$$

where $\sum_{k=1}^{N} m_{k,l} + \bar{m}_{H,l} + \tilde{m}_{H,l} = 1$; w_l^- and w_l^+ denote the lower and upper bound of the weight of j^{th} criterion.

Then, the interval-valued BPAs on L criteria are fused and normalized into interval-valued belief degrees by the following pair of nonlinear optimization models:

$$\max/\min \quad \xi_k(Z_i) = \frac{m_k}{1 - \bar{m}_H} \tag{64}$$

$$s.t. m_k = \rho \cdot [\prod_{l=1}^{L} (m_{k,l} + \bar{m}_{H,l} + \tilde{m}_{H,l}) - \prod_{l=1}^{L} (\bar{m}_{H,l} + \tilde{m}_{H,l})] \tag{65}$$

$$\tilde{m}_H = \rho \cdot [\prod_{l=1}^{L} (\bar{m}_{H,l} + \tilde{m}_{H,l}) - \prod_{l=1}^{L} \bar{m}_{H,l}] \tag{66}$$

$$\bar{m}_H = \rho \cdot [\prod_{l=1}^{L} \bar{m}_{H,l}] \tag{67}$$

$$\rho = [\sum_{k=1}^{N} \prod_{l=1}^{L} (m_{k,l} + \bar{m}_{H,l} + \tilde{m}_{H,l}) - (N-1) \cdot \prod_{l=1}^{L} (\bar{m}_{H,l} + \tilde{m}_{H,l})]^{-1} \tag{68}$$

$$m_{k,l}^- \le m_{k,l} \le m_{k,l}^+, k = 1, \ldots, N, l = 1, \ldots, L \tag{69}$$

$$\bar{m}_{H,l}^- \le \bar{m}_{H,l} \le \bar{m}_{H,l}^+, l = 1, \ldots, L \tag{70}$$

$$\tilde{m}_{H,l}^- \le \tilde{m}_{H,l} \le \tilde{m}_{H,l}^+, l = 1, \ldots, L \tag{71}$$

$$\sum_{k=1}^{N} m_{k,l} + \bar{m}_{H,l} + \tilde{m}_{H,l} = 1, l = 1, \ldots, L \tag{72}$$

After solving the above pair of nonlinear optimization models, we can obtain the interval-valued belief degree of alternative Z_i assigned to assessment grade H_k, which is denoted by $\xi_k(Z_i) = [\xi_k^-(Z_i), \xi_k^+(Z_i)]$, $k = 1, \ldots, N$. In addition, replacing the objective function $\xi_H(Z_i) = \frac{\tilde{m}_H}{1 - \bar{m}_H}$ with $\xi_k(Z_i) = \frac{m_k}{1 - \bar{m}_H}$, the unassigned interval-valued belief degree can be obtained, i.e., $\xi_H(Z_i) = [\xi_H^-(Z_i), \xi_H^+(Z_i)]$.

2) The ER nonlinear optimization models for generating interval-valued expected utility: After obtaining the overall interval-valued belief structure for each alternative, the ER algorithm provides several rules for generating the interval-valued expected utility. First, the assessment grades are ranked in ascending order according to their grade utility, where $u(H_1) \leq u(H_2) \leq \ldots \leq u(H_N)$. Then, the lower bound and upper bound of the interval-valued expected utility can be then calculated by solving the following pair of nonlinear optimization models:

$$\max u(S(Z_i)) = \sum\nolimits_{k=1}^{N} \xi_k(Z_i) \cdot u(H_k) + \xi_H(Z_i) \cdot u(H_N) \quad (73)$$

$$\min u(S(Z_i)) = \sum\nolimits_{k=1}^{N} \xi_k(Z_i) \cdot u(H_k) + \xi_H(Z_i) \cdot u(H_1) \quad (74)$$

$$s.t. \xi_k(Z_i) = \frac{m_k}{1 - \bar{m}_H} \quad (75)$$

$$\xi_H(Z_i) = \frac{\tilde{m}_H}{1 - \bar{m}_H} \quad (76)$$

$$m_k = \rho \cdot [\prod_{l=1}^{L} (m_{k,l} + \bar{m}_{H,l} + \tilde{m}_{H,l}) - \prod_{l=1}^{L} (\bar{m}_{H,l} + \tilde{m}_{H,l})] \quad (77)$$

$$\tilde{m}_H = \rho \cdot [\prod_{l=1}^{L} (\bar{m}_{H,l} + \tilde{m}_{H,l}) - \prod_{l=1}^{L} \bar{m}_{H,l}], l = 1, \ldots, L \quad (78)$$

$$\bar{m}_H = \rho \cdot [\prod_{l=1}^{L} \bar{m}_{H,l}], l = 1, \ldots, L \quad (79)$$

$$\rho = [\sum_{k=1}^{N} \prod_{l=1}^{L} (m_{k,l} + \bar{m}_{H,l} + \tilde{m}_{H,l}) - (N-1) \cdot \quad (80)$$

$$\prod_{l=1}^{L} (\bar{m}_{H,l} + \tilde{m}_{H,l})]^{-1} \quad (81)$$

$$w_l^- \cdot \xi_{k,l}^-(Z_i) \leq m_{k,l} \leq w_l^+ \cdot \xi_{k,l}^+(Z_i) \quad (82)$$

$$1 - w_l^+ \leq \bar{m}_{H,l} \leq 1 - w_l^- \quad (83)$$

$$w_l^- \cdot \xi_{H,l}^-(Z_i) \leq \tilde{m}_{H,l} \leq w_l^+ \cdot \xi_{H,l}^+(Z_i) \quad (84)$$

$$\sum_{k=1}^{N} m_{k,l} + \bar{m}_{H,l} + \tilde{m}_{H,l} = 1, l = 1, \ldots, L \quad (85)$$

Let $u^-(S(Z_i))$ and $u^+(S(Z_i))$ be the optimal objective function values of the above pair of nonlinear programming models, which respectively denotes the lower and upper bound of the interval-valued expected utility.

C. An improved minimax regret approach to compare the interval-valued expected utilities

Since the expected utilities are characterized by interval values, we cannot directly compare and rank them. So, a reasonable interval-valued ranking approach is necessary. Many studies have attempted to rank the interval values from different perspectives, but most of them fail to rank the interval values when they share the same center but different widths. To address this situation, Wang et al. [69] developed a minimax regret (MR) approach.

Definition 1 ([69]): Let $I_j = [I_j^-, I_j^+] (j = 1, \ldots, N)$ be N interval-valued expected utilities. The maximum primary regret (MPR) degree of interval-valued expected utility I_k (also called maximum primary loss of expected utility I_k) can be calculated by:

$$MPR(I_k) = \max[\max_{j \neq k}(I_j^+) - I_k^-, 0], j = 1, \ldots, N \quad (86)$$

The interval-valued expected utility with the smallest maximum MPR degree is selected as the most desirable one. To further generate the complete ranking order of all interval-valued expected utilities, Wang et al. [69] introduced the following eliminating steps:

Step 1. Calculate the MPR degree of each interval-valued expected utility and select the one with the minimum MPR degree as the best interval-valued expected utility. Suppose I_{k_1} is selected as the best one, where $1 \leq k_1 \leq N$.

Step 2. Eliminate I_{k_1} from further consideration and re-calculate the MPR degree of the remaining interval-valued expected utilities. Suppose I_{k_2} has the minimum MPR degree, where $1 \leq k_2 \leq N$..

Step 3. Repeat the above processes until only one interval-valued expected utility is left. The final ranking order of the N interval-valued expected utilities is $I_{k_1} \succ I_{k_2} \succ \cdots \succ I_{k_N}$, where $\succ$ means 'be superior to'.

Although the MR approach can distinguish the interval values with equal center but different widths, there is still one outstanding problem, that is, the MR approach may lose some useful information. We provide a simple example to intuitively explain this viewpoint.

Example 1: Suppose that there are three interval values $I_1 = [0.4, 0.7]$, $I_2 = [0.4, 0.6]$ and $I_3 = [0.1, 0.9]$. When we use the MR approach to rank the three interval values, the MPR degree of each interval value is calculated as follows:

$$MPR(I_1) = \max[\max\{0.6, 0.9\} - 0.4, 0] = 0.5$$
$$MPR(I_2) = \max[\max\{0.7, 0.9\} - 0.4, 0] = 0.5$$
$$MPR(I_3) = \max[\max\{0.6, 0.7\} - 0.1, 0] = 0.6$$

Then, the minimax primary regret degree is determined as $\min\{MR(I_1), MR(I_2), MR(I_3)\} = 0.5$ and the ranking order is $I_1 \approx I_2 \succ I_3$. We can observe that the MR approach fails to distinguish the two different interval values I_1 and I_2, the reason is that the right endpoint information of interval values I_1 and I_2 is ignored. To tackle this deficiency, we tend to propose an IMR approach by making some improvements to the MR approach.

Suppose that there are N interval values $I_j = [I_j^-, I_j^+] (j = 1, \ldots, N)$ and $I_k = [I_k^-, I_k^+]$ is selected as the final one. If $I_k^- < \max_{j \neq k}(I_j^+)$, the decision maker may feel regret and the MPR degree he/she may suffer can be measured by the following equation:

$$MPR(I_k) = \max[\max_{j \neq k}(I_j^+) - I_k^-, 0], j = 1, \ldots, N \quad (87)$$

Logically, the interval value sharing the minimax primary regret degree should be determined as the optimal one, the minimax primary regret degree among all interval values is calculated by the following rule:

$$\min_k \{MPR(I_k)\} = \min_k \{\max[\max_{j \neq k}(I_j^+) - I_k^-, 0]\} \quad (88)$$

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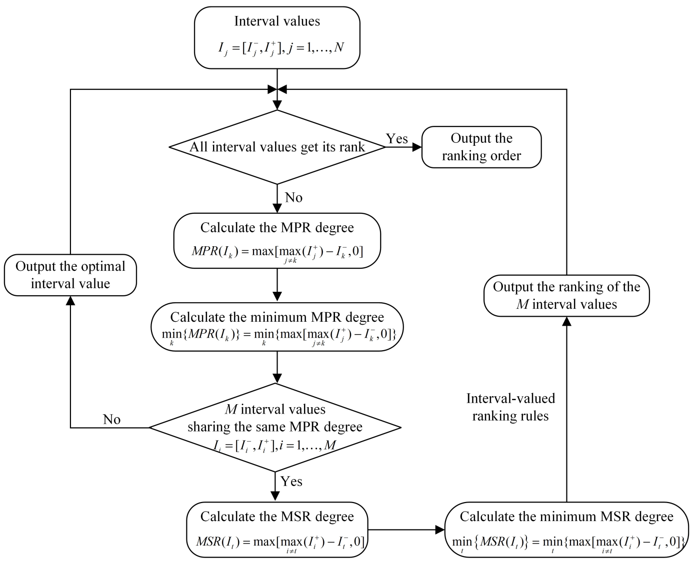

Fig. 5. The flowchart of the IMR approach

If there are several interval values $I_i = [I_i^-, I_i^+]$ ($i = 1, \ldots, M, M \leq N$) sharing the same minimax primary regret degree, we can further distinguish them by calculating the minimax secondary regret degree. Suppose $I_t = [I_t^-, I_t^+]$ is the final one selected from the M interval values. The maximum secondary regret (MSR) degree can be calculated by the following equation:

$$MSR(I_t) = \max[\max_{i\neq t}(I_i^+) - I_t^-, 0], i = 1, \ldots, M \quad (89)$$

After obtaining the MSR degree, the minimax secondary regret degree is determined by the following rule:

$$\min_t \{MSR(I_t)\} = \min_t\{\max[\max_{i\neq t}(I_i^+) - I_t^-, 0]\} \quad (90)$$

In summary, the following rules are developed to compare and rank the interval values:

(1) If $\min\{MPR(I_k)\} < \min\{MPR(I_j)\}$ ($j = 1, \ldots, N$, $j \neq k, k = 1, \ldots, N$), then interval value I_k is considered to be superior to interval value I_j.

(2) If $\min\{MPR(I_k)\} = \min\{MPR(I_t)\} < \min\{MPR\ (I_j)\}(j \neq k \neq t, k = 1, \ldots, N, t = 1, \ldots, N)$, the minimax secondary regret degrees of $I_k = [I_k^-, I_k^+]$ and $I_t = [I_t^-, I_t^+]$ are calculated to distinguish them.

(2.1) If $\min\{MSR(I_k)\} < \min\{MSR(I_t)\}(k \neq t, k = 1, \ldots, N, t = 1, \ldots, N)$, then I_k is better than I_t and the ranking of the three interval values is $I_k \succ I_t \succ I_j$.

(2.2) If $\min\{MSR(I_k)\} > \min\{MSR(I_t)\}(k \neq t, k = 1, \ldots, N, t = 1, \ldots, N)$, then I_k is better than I_t and the ranking of the three interval values is $I_t \succ I_k \succ I_j$.

(2.3) If $\min\{MSR(I_k)\} = \min\{MSR(I_t)\}(k \neq t, k = 1, \ldots, N, t = 1, \ldots, N)$, then I_k is equal to I_t and the ranking of the three interval values is $I_k \approx I_t \succ I_j$.

A flowchart is given in Fig.5 to better illustrate the process of implementing the IMR approach.

To show the superiority of the IMR approach over the MR approach, we use it to solve the Example 1 again. The processes are summarized as follows:

Step 1: Calculate the MPR of each interval value. The results are shown as follows:

$$MPR(I_1) = \max[\max\{0.6, 0.9\} - 0.4, 0] = 0.5$$
$$MPR(I_2) = \max[\max\{0.7, 0.9\} - 0.4, 0] = 0.5$$
$$MPR(I_3) = \max[\max\{0.6, 0.7\} - 0.1, 0] = 0.6$$

From the results, we can observe that both the interval values I_1 and I_2 have the smallest MPR degree.

Step 2: Eliminate I_3 from the further consideration and the temporary ranking of the three interval values is $I_1 \approx I_2 \succ I_3$.

Step 3: Distinguish the interval values I_1 and I_2 by calculating the MSR degrees of I_1 and I_2.

$$MSR(I_1) = \max[\max\{0.6\} - 0.4, 0] = 0.2$$
$$MSR(I_2) = \max[\max\{0.7\} - 0.4, 0] = 0.3$$

Since $MSR(I_1) < MSR(I_2)$, the interval value I_1 is selected as the best one and the complete ranking order of the three interval values is $I_1 \succ I_3 \succ I_2$.

In summary, compared to the MR approach, our approach can effectively distinguish the two different interval values I_1 and I_2, and produce a more reasonable ranking order.

V. THE EVCS SITE SELECTION FRAMEWORK BASED ON MULTI-GRANULAR HETEROGENEOUS INFORMATION

To better understand the proposed decision-making framework, this subsection provides a diagram to illustrate its implementation process, as shown in Fig.6. Specifically, the proposed decision-making framework consists of three stages: i) information unification, ii) information fusion, and iii) alternatives ranking, which are further detailed below.

Stage 1. Information unification. The evaluation information under different kinds of criteria is usually characterized by different forms, e.g., quantitative criteria are expressed by numerical data whereas qualitative criteria are represented by linguistic terms. Moreover, the linguistic terms elicited by different decision makers are usually defined on multi-granular linguistic term sets. To make decisions with heterogeneous information and multi-granular linguistic terms, the information transformation mechanisms provided in subsection IV-A are used to unify them. After the unification, the original evaluation values are transformed into the interval-valued belief structures defined on set of general fuzzy assessment grades $\Omega = \{H_1, \ldots, H_N\}$ and $S(H_k(r_{il})) = \{(H_k, [\xi^-(r_{il} \in H_k), \xi^+(r_{il} \in H_k)]), k = 1, \ldots, N\}$.

Stage 2. Information fusion. After information transformation and unification, we can fuse the evaluation information by the extended ER algorithm to generate the aggregated opinion of each alternative. First, by combining with the criteria weights, the interval-valued belief structures are transformed into interval-valued BPAs. A pair of nonlinear optimization models are then constructed to fuse the interval-valued BPAs on L criteria. Eventually, by solving a pair of nonlinear optimization models, the interval-valued expected utility of each alternative is obtained as $u(S(Z_i)) = [u^-(S(Z_i)), u^+(S(Z_i))]$, $i = 1, \ldots, M$.

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Stage 3. Alternative ranking. Considering that the interval values are hard to compare and rank, this paper proposes an IMR approach to compare and rank the obtained interval-valued expected utilities. Though the IMR approach, the complete ranking order of the interval-valued expected utilities can be generated as: $u(S(Z_{i_1})) \prec u(S(Z_{i_2})) \prec \ldots \prec u(S(Z_{i_M}))$. Accordingly, the ranking order of the alternatives are obtained as: $Z_{i_1} \prec Z_{i_2} \prec \ldots \prec Z_{i_M}$.

The specific decision procedures of the proposed decision-making framework are summarized in Algorithm 1.

Algorithm 1 The specific decision procedures of the proposed decision-making framework

Input. The original evaluation value r_{il}^{p} and the set of general assessment grade $\Omega = \{H_1, \ldots, H_N\}$.
Output. The ranking order of all alternatives.
Stage 1. Information unification
Step 1. Select a collectively exhaustive and mutually exclusive set of general assessment grades and encode them into shadowed sets by the computing with words model provided in subsection III-B.
Step 2. Through the three information transformation mechanisms established in subsection IV-A, the crisp values, interval values, and multi-granular linguistic terms are unified into the interval-valued belief structures.
Stage 2. Information fusion
Step 3. To reflect the importance of the evidences, the interval-valued belief degrees need to be transformed into interval-valued BPAs via Eqs. (59)-(63).
Step 4. Based on the nonlinear optimization models Eqs. (64)-(72), the interval-valued BPAs on all decision-makers can be fused and normalized into interval-valued belief degrees with respect to the L criteria.
Step 5. The obtained interval-valued belief degrees can be conducted into interval-valued BPAs on L criteria, and then normalized into overall interval-valued belief degrees by the nonlinear optimization models Eqs. (64)-(72).
Step 6. A pair of nonlinear optimization models Eqs. (73)-(85) is developed to generate the interval-valued expected utility of each alternative.
Stage 3. Alternative ranking
Step 7. An IMR approach is proposed to compare and rank the obtained interval-valued expected utilities.
Step 8. According to the outcomes of the IMR approach, the ranking order of alternatives is obtained.
End

VI. CASE STUDY

This section provides a realistic EVCS site selection example together with comparisons to illustrate the detailed implementation process in a group decision scheme [20], [70] and the advantages of the proposed decision-making framework.

A. Problem description

To achieve sustainable development goals in the transportation system, China has been devoted to popularizing electric vehicles. According to the "Automotive Big Data Application Research Report (2021)" issued by the Social Sciences Academic Press, the annual sales volume of electric vehicles in China is expected to reach 5.3 million by 2025. The rapidly growing number of electric vehicles has created a huge demand for charging infrastructure. Selecting the appropriate EVCS location is the primary task for establishing charging infrastructure. To illustrate the effectiveness and flexibility of the proposed decision-making framework in solving EVCS site selection problems, a case study about Shenzhen, China is carried out. The reason for choosing Shenzhen as a case study is that Shenzhen is the leading city in terms of the number and promotion of electric vehicles.

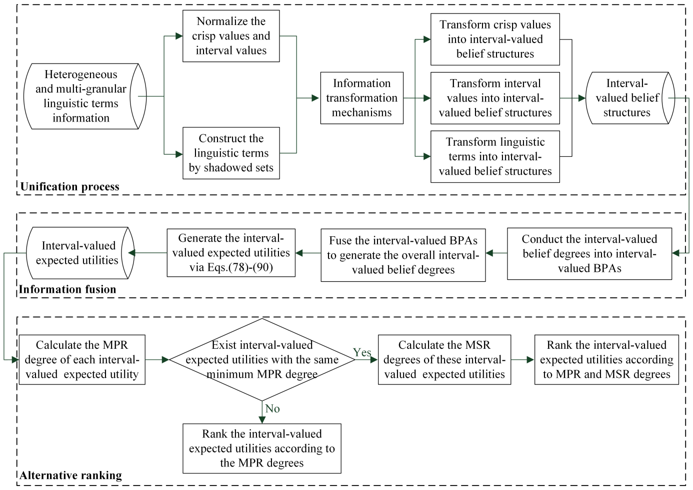

Fig. 6. The flowchart of the proposed decision-making framework

To meet the growing number of electric vehicles, the Shenzhen government plans to build a new EVCS with an area of 4500-square-meter and 50 charging piles. The total rated power and maximum service capacity of this EVCS are approximately 3000kW and 600 electric vehicles per day, respectively. After a preliminary discussion and investigation, the government decides to select a EVCS site from the following five districts, i.e., Nanshan (Z_1), Futian (Z_2), Baoan (Z_3), Pingshan (Z_4) and Luohu (Z_5), as shown in Fig.7. In practice, the EVCS site selection is usually influenced by multiple criteria from several dimensions. According to the literature review and expert interviews, this paper selects ten criteria from three dimensions (see Table II (see appendix B)) to comprehensively reflect the characteristics of EVCS site selection. These criteria can be divided into two categories, i.e., quantitative criteria and qualitative criteria.

Due to the scarcity of evidential data in EVCS site selection, we use expert judgments to strengthen and complement our analysis. Three experts respectively from the governmental institution, environmental organization, and academic institution are invited to provide their assessments of different EVCS sites. The profiles of the experts' panel are provided in Table III (see appendix B). To provide a reference for the assessment, some related EVCS data of Shenzhen in 2020 are investigated and summarized in Table IV (see appendix B). Moreover, due to the difference in experience and knowledge,

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the linguistic terms elicited by different experts are usually defined on multi-granular linguistic term sets, as shown in Table V (see appendix B).

The evaluation information of alternatives with respect to the different criteria is collected and summarized in Table VI-VIII [1] (see appendix B). From Table VI-VIII, we can observe that the quantitative criteria are expressed by numerical data (crisp values or interval values) and the qualitative criteria are expressed by multi-granular linguistic terms. Specifically, the numerical data are generated based on the data presented in Table IV and experts' knowledge while the multi-granular linguistic terms are elicited by experts according to their knowledge and experience. For accomplishing computing with words processes, this paper employs the shadowed sets to encode the multi-granular linguistic terms and the corresponding results are shown in Table IX (see appendix B) [57], [71].

B. Implementation

We herein implement the steps provided in Algorithm 1 to select the optimal EVCS site for Shenzhen city.

Step 1. Select a collectively exhaustive and mutually exclusive set of general assessment grades and encode them into shadowed sets. The selected general assessment grades and their corresponding shadowed sets and expected utilities are listed in Table X (see appendix B).

Step 2. Conduct the crisp values, interval values and multi-granular linguistic terms into interval-valued belief degrees distributed on a set of general assessment grades though the proposed information transformation mechanisms.

Step 3. Construct the interval-valued BPAs by combining the experts weights and the interval-valued belief degrees based on Eqs. (59)-(63). In this paper, these three experts are considered equally important.

Step 4. Based on the nonlinear optimization models Eqs. (64)-(72), the interval-valued belief degrees of each alternative on L criteria can be calculated and obtained.

Step 5. The obtained interval-valued belief degrees can be conducted into interval-valued BPAs on L criteria via Eqs.(59)-(63), and then fused by Eqs.(64)-(72) to generate the overall interval-valued belief degree of each alternative. The criteria weights are provided by experts, which are $w_{11} = [0.658, 0.982]$, $w_{12} = [0.235, 0.566]$, $w_{13} = [0.013, 0.269]$, $w_{14} = [0.223, 0.446]$, $w_{21} = [0.596, 0.643]$, $w_{22} = [0.241, 0.944]$, $w_{23} = [0.196, 0.352]$, $w_{31} = [0.638, 0.844]$, $w_{32} = [0.428, 0.956]$ and $w_{33} = [0.235, 0.427]$.

Step 6. Calculate the interval-valued expected utility of each alternative by the nonlinear optimization models Eqs.(73)-(85). The results are $u(S(Z_1)) = [0.25, 1.432]$, $u(S(Z_2)) = [0.284, 1.355]$, $u(S(Z_3)) = [0.29, 1.395]$, $u(S(Z_4)) = [0.398, 1.373]$ and $u(S(Z_5)) = [0.234, 1.421]$.

Step 7. Compare and rank the obtained interval-valued expected utilities by the IMR approach. The corresponding ranking order is $u(S(Z_4)) > u(S(Z_3)) > u(S(Z_2)) > u(S(Z_1)) > u(S(Z_5))$.

[1]All these data are collected in 2021 through experts interviews.

Step 8. Output the decision results. The ranking order of alternatives is $Z_4 \succ Z_3 \succ Z_2 \succ Z_1 \succ Z_5$ and the best site for establishing charging infrastructure is Pingshan (Z_4).

C. Comparisons

This subsection shows the advantages of the proposed decision-making method through a comparative analysis with some previous studies. Two representative decision-making methods are selected for comparison: the multi-source heterogeneous data-based decision-making (MSHDM) method [15] and the multi-granular heterogeneous information-based decision-making (MGHDM) method [71]. The main characteristics of these two methods and the proposed method are summarized in Table XI.

TABLE XI
THE MAIN CHARACTERISTICS OF DIFFERENT METHODS

Methods	Criteria information	Linguistic terms modeling	Heterogeneous information transformation	Ways of alternatives ranking
MSHDM method	Heterogeneous information	Trapezoid fuzzy sets	Transformation based on deviation degree	Choquet integral values
MGHDM method	Heterogeneous information	Shadowed sets	Transformation based on distributed assessment framework	Expected utilities
Proposed method	Heterogeneous information	Shadowed sets	Transformation based on interval-valued distributed assessment framework	IMR approach

From Table XI, we can observe that there are some differences between the proposed method and the selected methods, mainly focusing on heterogeneous information transformation, linguistic terms modeling, and alternatives ranking. To intuitively explain these differences, the following quantitative comparisons are conducted.

(1) *Comparison between the proposed method and the MSHDM method.* To compare our method with the MSHDM method proposed by Yuan et al. [15], we apply our method to their example, which aims to determine the optimal distributed energy system for Henan Province. In this example, six alternatives are evaluated with respect to ten criteria by crisp values, interval values, and linguistic terms. The data and parameter values used can be seen in [15]. The comparison results are presented in Table XII.

TABLE XII
THE COMPARISON RESULTS OF THE PROPOSED METHOD AND THE MSHDM METHOD

The proposed method			MSHDM method		
Alternatives	Ranking values	Rankings	Alternatives	Ranking values	Rankings
Z_1	[0.023, 2.264]	5	Z_1	0.0704	6
Z_2	[0.028, 2.012]	6	Z_2	0.1331	5
Z_3	[0.035, 2.288]	4	Z_3	0.3292	2
Z_4	[0.021, 3.133]	1	Z_4	0.279	4
Z_5	[0.121, 2.173]	2	Z_5	0.4101	1
Z_6	[0.053, 2.273]	3	Z_6	0.3078	3

Obviously, the results obtained by the proposed method and MSHDM method are different. The main reasons for the difference can be summarized as: (1) The way of modeling linguistic terms is different. In [15], the linguistic terms are modeled by

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trapezoid fuzzy sets while our study models them by shadowed sets. The shadowed sets can simultaneously reflect the uncertainty and personalized individual semantics of linguistic terms and produce more reliable linguistic processing results. (2) The way of heterogeneous information transformation is different. In [15], the heterogeneous information is transformed into crisp values, which may cause serious information loss. In contrast, the distributed assessment framework used in this paper can preserve maximum information elicited by experts in the initial stage [20]. (3) The way of alternatives ranking is different. In this paper, the decision results are characterized by interval values and ranked by the IMR approach, which is beneficial for improving the reliability of decision results.

(2) *Comparison between the proposed method and the MGHDM method.* To ensure the fairness and rationality of comparison, we applied the proposed method to the example presented in [71]. This example is about selecting the most appropriate waste-to-energy technology from five alternatives. In the selection process, three experts are invited to express their opinions on alternatives with respect to six criteria by crisp values, interval values, and linguistic terms. The data and parameter values used can be seen in [71]. The comparison results are presented in Table XIII.

TABLE XIII
THE COMPARISON RESULTS OF THE PROPOSED METHOD AND MGHDM METHOD

The proposed method			MGHDM method		
Alternatives	Ranking values	Rankings	Alternatives	Ranking values	Rankings
Z_1	[0.098, 1.235]	3	Z_1	0.505	4
Z_2	[0.126, 1.607]	1	Z_2	0.906	1
Z_3	[0.069, 1.586]	4	Z_3	0.557	3
Z_4	[0.086, 1.567]	5	Z_4	0.48	5
Z_5	[0.117, 1.508]	2	Z_5	0.619	2

From Table XIII, we can observe that the best alternative and worst alternative obtained by the MGHDM method and our method are the same, but the positions of other alternatives are different. This indicates that the proposed method can effectively select the optimal alternative, but there exist some differences with the MGHDM method. The main reason for such difference is that the proposed method characterizes the distributed assessment information by interval values instead of crisp values. Compared to the crisp values, the interval values can better manage the uncertainty and preserve more initial information. Thus, it seems logical that the results obtained by our method are more reasonable and reliable.

D. Policy implications

In this paper, a new decision-making framework is proposed to select the optimal EVCS location in Shenzhen (China) within the context of heterogeneous information and multi-granular linguistic terms. The outcomes of the case study offer some managerial insights concerning the EVCS site selection and sustainable transport.

First, when governments determine the site of constructing EVCS, they should not only consider a single criterion, which might be very easy to bias the result. EVCS site selection is a multi-dimensional complex problem, which usually involves multiple criteria from several dimensions, e.g., economy, society, and environment. The MCDM methods are identified as the most appropriate tools to balance the influences of these criteria. Hence, selecting a suitable MCDM method and EVCS site selection criteria can make the results more convincing.

Second, the evaluation information formats under different criteria are usually different, and the linguistic terms elicited by different experts are usually defined on multi-granular linguistic term sets. Thus, how to process heterogeneous information and multi-granular linguistic terms is of great importance. Besides, choosing different information processing tools will have significant impact on the selection results. As stated in the comparisons, the shadowed sets can more effectively reflect the personalized individual semantics of linguistic terms and the interval values can better describe the uncertainty. Hence, a decision-making method based on shadowed sets and interval-valued distributed assessment is suggested for the EVCS site selection.

Third, the sustainable EVCS needs to be environmentally friendly, economically sustainable, and people-oriented. To achieve this goal, the policymakers should implement strict environmental standards for the construction and operation of EVCS to protect the environment. Meanwhile, some preferential policies should be executed to protect investors' interests, such as exempting tax, direct subsidies, and shortening construction and payback period. Moreover, the governments (or investors) and the policymakers should benefit the residents by the EVCS to improve their acceptance of EVCS, achieving the transformation from "Not In My Back Yard" to "Beauty In My Back Yard" [72].

VII. CONCLUSIONS

To alleviate the energy crisis and reduce carbon dioxide emissions, the Chinese government is committed to developing electric vehicles. The EVCS site selection is one of the most critical managerial decisions in the field of electric vehicle management. In this paper, a new decision-making framework is proposed to solve the EVCS site selection problems. In the proposed framework, three information transformation mechanisms are established to unify the information under different criteria and elicited by different experts. In addition, with the aid of ER algorithm, a new information fusion method is proposed to generate the interval-valued expected utilities of alternatives. As an improvement of the MR approach, an IMR approach is developed to compare and rank the interval-valued expected utilities.

To check the effectiveness and applicability of the proposed framework, it is implemented in a case study of the EVCS location selection problem within the context of heterogeneous information and multi-granular linguistic terms. The data were collected from various official institutions and expert interviews. The results confirm that the proposed decision-making framework can help investors and governments in improving their decision processes, especially when the evaluation information is expressed by uncertain measurements. To validate the results, the proposed framework is also compared with some representative methods. The obtained outcomes highlight the potential and advantages of the proposed framework in dealing with EVCS location selection problems.

Even though, this paper has made important contributions to solving EVCS site selection problems, there are still some limitations to be considered in our future research. (1) This paper assumes that criteria are complete independent, however, there are usually some interrelationships among different criteria. (2) In practice, the evaluation information provided by different experts may be inconsistent. However, this paper fails to consider this characteristic. (3) This paper ignores the influence of experts' psychological behaviors on the decision results.

The proposed framework will serve as an effective tool for selecting an optimal EVCS site under multiple criteria conditions and uncertain environments. In future studies, some interaction operators should be introduced to consider the interrelationships among multiple criteria. Further studies will also focus on using consensus-reaching models to guide experts to modify their opinions to improve the level of consensus. Moreover, some behavior decision methods such as prospect theory, TODIM method, and regret theory can also be extended into EVCS site selection to describe the psychological behaviors of experts, and then enhance the reliability and rationality of the results. In the future, we will also study the application of the proposed framework to solve other similar problems, e.g., green supplier selection, waste to energy plant site selection, renewable energy evaluation, and others.

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