Research Article

Tackling Complexity in Green Contractor Selection for Mega Infrastructure Projects: A Hesitant Fuzzy Linguistic MADM Approach with considering Group Attitudinal Character and Attributes' Interdependency

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Continuous environmental concerns regarding construction industry have been driving general constructors of mega infrastructure projects to incorporate green contractors. Although conventional multiple attributes decision-making (MADM) methodologies have provided feasible ways to select contractor, high complexity in scenarios of megaprojects still challenges existing MADM methods in concurrently accommodating three key issues of decision hesitancy, attributes interdependency, and group attitudinal character. To elicit decision-makers' hesitant fuzzy assessments more objectively and comprehensively, we define an expression tool called interval-valued dual hesitant fuzzy uncertain unbalanced linguistic set (IVDHF_UUBLS) and develop aggregation operators through its operations. To exploit attributes interdependency, we establish a synthesized attributes' weighting model to fuse an attributes interdependency-based weighting vector and an argument-dependent weighting vector, which are, respectively, derived through Decision-Making and Trial Evaluation Laboratory (DEMATEL) technique and maximizing deviation method. To effectively utilize decision-makers' group attitudinal characters, we also develop a TOPSIS-based method to rationally transform group ideal attitudes into order-inducing vectors. On the strength of the above methods, an integrated MADM approach is then constructed. Finally, illustrative case study and experiments are conducted to validate our approach.

1. Introduction

In comparison with other industries, the industry of construction has been observed as exerting major contribution to environmental pollution [1], including those related to noise, air, solid waste, and water pollution. [2, 3]. The problems of construction pollution and wastes have been more critical in countries that are undertaking accelerated urbanization construction with high growth rate of economics. As can be seen, the environmental concerns especially stand out for mega infrastructure construction projects because those megaprojects are basically one-off and sustaining in a relatively very long period [4, 5]. As a matter of fact, mega infrastructure construction projects are assumed to take responsibility

to minimize their negative impact on environments when maximizing contribution to economics and society. To that end, not only high level of project management sophistication is needed but a nexus of green contractors also should be incorporated in project organization [6]. As a result, green contractor selection plays a strategically important role in achieving success of megaprojects.

Due to self-evident complexity in large-scale projects like mega infrastructure, understanding scenarios of work packages and selecting appropriate contractors are intrinsically complicate [7, 8]. To confront the complexity in contractor selection, Safa et al. [5] suggested utilizing results of competitive intelligence (CI) systems as favorable inputs

to multiple attributes decision-making (MADM) methodologies. However, during contractor selection activities at the front end planning phase [9], decision-makers' assessments inevitably characterize with vagueness and uncertainty due to limitedness in their experience, knowledge and expertise [10, 11]. To help decision-makers decrease complexity under different scenarios of green contractor selection, pioneering researches have introduced effective MADM approaches that integrate uncertainty expression tools, such as fuzzy sets [12] and linguistic sets [13–15]. BuiThiNuong et al. [16] put forward a fuzzy AHP method to accommodate contractor selection with imprecise information. Kusi-Sarpong et al. [17] developed a joint rough sets and fuzzy TOPSIS method. Zavadskas et al. [18] presented a weighted aggregated sum product assessment method which uses grey values for contractor selection. When facing more complicate contractor selection problems with ill-structured definition, Vahdani et al. [19] devised an ideal solutions-based MADM approach to contractor selection by employing linguistic variables to describe uncertain assessments. Alhumaidi [20] utilized linguistic variables to construct a fuzzy-logic based multiple attributes group decision-making method. Most recently, in viewing of common phenomena of decision hesitancy in complex decision-making processes [21, 22], Borujeni and Gitinavard [23] studied a group decision-making approach based on hesitant fuzzy preference relations.

Actually, advocating practicality of hesitant fuzzy set (HFS) [21], one of popular research directions in fuzzy MADM literature has also focused on tackling complicate situations with decision hesitancy based on HFS [40]. Such as the MADM approach based on Shapley-Choquet integral operators to consider interdependencies among attributes [41], the hesitant fuzzy TOPSIS method [42], the MADM approach based on hesitant fuzzy Hamacher aggregation [43], the hesitant fuzzy QUALIFLEX approach [44], among others. Following the idea of HFS, Zhu et al. [45] extended HFS to the dual hesitant fuzzy set (DHFS) by adding nonmembership degrees in depicting hesitancy. Since then, DHFS has been studied with a deep extent, such as those listed in [46–50]. Regarding decision-making situations where linguistic variables gain feasibility and adaptability, on the basic ideas of HFS, Rodríguez et al. [51] firstly introduced the hesitant fuzzy linguistic term sets to allow decision hesitancy of possible linguistic terms. However, in practical cases, decision-makers are capable of reaching the most favorite linguistic label but generally holding decision hesitancy to that label; or under the decision-making situations where voting and majority rule apply, group opinions will locate at a linguistic label or a linguistic interval [52] but obviously there exists decision hesitancy to the voted label. As a result, compound expression tools of hesitant fuzzy linguistic sets and their MADM approaches have attracted widespread interests. Such as, hesitant fuzzy linguistic set [38, 53] and dual hesitant fuzzy linguistic set [39, 54], among others. Comparatively, compound hesitant fuzzy linguistic expression tools attain more adaptability and feasibility in practical complex decision environments.

Although researches in both contractor selection literature and MADM literature have presented rich approaches

for application to green contractor selection problems, there is still a gap with three facets to be further investigated concurrently. First, most of existing hesitant fuzzy linguistic expression tools were based on rigidly uniform or symmetrical linguistic label sets [55, 56]; however, practical studies [57, 58] have revealed that decision-makers are inclined to express their complicate assessments more precisely and objectively by use of non-uniform or asymmetric linguistic term set, that is, the unbalanced linguistic term set (ULTS) [59]. Second, under complicate decision-making environments, interdependency among attributes is a serious issue that needs to be addressed [60]. However, Choquet integral incorporated by Lin et al. [38] can only capture interactions between adjacent coalitions, while the prioritized aggregation operator in [53, 54] requires linear ordering of evaluative attributes that is often difficult for decision-makers to deduce up front in complex practices. Third, in order to deal with real-world complex problems, various degrees of optimism (degree of orness) of decision-makers should be coordinated as complex attitudinal characters and taken into account during decision-making [61]. Merigó and Casanovas [61] suggested to use order-inducing variables for reflecting complex attitudinal characters and integrate them into information aggregation operators, in which the order-inducing variables are usually not directly defined and need to be derived appropriately [62]. But to our best knowledge, thus far, there is scarcely any attention has been paid to the complex attitudinal characters when tackling complicate contractor selection problems.

Therefore, to bridge the above-discussed gap, we first introduce an interval-valued dual hesitant fuzzy uncertain unbalanced linguistic set (IVDHF_UUBLS) whose elements hold a hybrid structure of $\langle x, \tilde{s}, \tilde{h}(x), \tilde{g}(x) \rangle$, in which two interval-valued fuzzy sets $\tilde{h}(x)$ and $\tilde{g}(x)$ denote possible membership and nonmembership degrees to the uncertain unbalanced linguistic term $\tilde{s}$. IVDHF_UUBLS can depict fuzzy properties of an object more comprehensively and flexibly. We also develop a series of generalized aggregation operators for IVDHF_UUBLS. In order to exploit interdependency relations among evaluative attributes more effectively, we next employ the Decision-Making and Trial Evaluation Laboratory (DEMATEL) [63, 64] to capture both direct and indirect influences between attributes, thereby constructing a more rational attributes weighting model. To include decision-maker's complex attitudinal characters, instead of assuming subjective values, we propose a robust TOPSIS-based method to identify the order-inducing variables based on positive and negative ideal attitudes. On the strength of above methods, we subsequently propose an effective MADM approach for resolving the complex problems of green contractor selection.

The rest of this paper is organized as follows. In Section 2, research problem is described. Section 3 defines the new hybrid hesitant fuzzy linguistic expression tool, i.e., IVDHF_UUBLS, and studies basic operations and distance measure for IVDHF_UUBLS. Section 4 investigates several fundamental generalized aggregation operators for

IVDHF_UUBLS. In Section 5, We detail the DEMATEL-based model for weighting evaluative attributes and the TOPSIS-based method for deriving order-inducing variables, based on which we then construct an effective approach for complex MADM. In Section 6, illustrative case study and experiments are further conducted to verify the proposed MADM approach. Finally, conclusions and future research are presented in Section 7.

2. Description of Research Problem

The significant impacts of construction activities on the environment have triggered serious alarms and governments worldwide have introduced various policies, regulations and industrial evaluation systems for controlling them [65], for instance, the cleaner production promotion law and the pollution prevention law in China and the green building rating systems in the US, UK, and China [66]. To meet the requirements of environmental concerns, construction projects have to select contractors in operations by simultaneously considering potential contractors' green characteristics [6]. Actually, the practical needs of selecting green contractors are especially indispensable for mega infrastructure construction projects as they generally are one-off and nearly ever-lasting in the environment.

2.1. Evaluative Attributes for Green Contractor Selection. Typically, when construction organizations seek to develop appropriate approaches to contractor selection, the organizations' specific requirements are firstly introduced. Therefore, different sets of evaluative attributes for contractor selection with different scenarios are needed. During last two decades, many efforts have been paid to identify selection attributes and construct comprehensive contractor selection methods with different applications [8, 10, 18, 19, 23, 24, 26, 28, 67, 68].

One basic observation from existing literature for considering evaluative attributes is that, being analogous to selecting suppliers in supply chain management [69], decision-makers are supposed to not only consider competitive capability that distinguishes contractors from each other by business operations, but also examine contractor's cooperation capacity with other partner contractors that indeed influences the project success [8, 70]. More importantly, since the construction industry has great impact on environment and the governments worldwide have introduced various policies and regulations for controlling them [6], green practices thus has become a crucial facet for evaluating green contractors [68, 71]. As a result, three aspects of business competitiveness, cooperation, and green practices thus become indispensable to derive evaluative attributes for green contractor selection.

Many earlier studies put their emphasis on competitive attributes to evaluate comprehensive performance of contractors. Hatush and Skitmore [26] suggested five competitive attributes to assess contractors, including financial soundness, technical ability, management capability, health and safety, and reputation. Fong and Choi [24] studied contractor selection problem for Hong Kong scenario and derived a set

of eight evaluative attributes according to a questionnaire survey, among which seven are competitive attributes including price, financial capability, past performance, past experience, resource, current workload, and safety performance. In their developed computer-aided decision support system, Shen et al. [28] employed a parameter system to evaluate contractor's competitiveness in the Chinese construction industry, in which six competitive attributes were included as social influence, technical ability, financing ability and accounting status, marketing ability, management skills, and organizational structure and operations. Darvish et al. [25] developed a graph theory-based decision-making method to cope with contractor prequalification problem under Iranian scenarios; they introduced the Iranian domestic prequalification criteria system that included nine main indicators: work experience, technology & equipments, management, experience and knowledge of the operation team, financial stability, quality, being familiar with the area or being domestic, reputation, and creativity and innovation. Nieto-Morote and Ruz-Vila [10] also investigated a fuzzy decision-making model based on TOPSIS to accommodate construction contractor prequalification problem; they summarized the most common factors for comprehensively considering contractors during the prequalification that fall into following main aspects: technical capacity, experience, management capability, financial stability, past performance, past relationship, reputation, and occupational health & safety. Focusing on contractor selection problems in Lithuania construction industry, Zavadskas et al. [18] proposed an effective multiple attributes decision-making approach called WASPAS-G, in which main attributes are identified to cover: bid amount, capability & skill, occupational health and security, technical capacity, managerial capacity, past performance, and past experience. As seen from the above representative literature, quotation, technical strength and resource strength are the three main factors which are widely accepted and adopted; we thus include these factors as main evaluative attributes in this paper. Another finding from the above reviewed literature is that nearly all of them emphasized the inclusion of indicators to examine credibility of contractors in their managing external and internal challenges [72, 73], such as financial capability [24], safety performance [24], and reputation [10, 25, 26]; therefore, we introduce the 'Credibility' as another main attribute in this paper.

Indeed, cooperation attributes must be taken into consideration because cooperation among selected contractor influences the project success [74]. Actually, some of earlier pioneering studies also noticed and took consideration of cooperation attribute in their parameter systems, such as 'client/contractor relationship' in references [10, 24]. Recently, increasing attentions have been paid to investigate appropriate evaluative cooperation attributes for contractor selection. Representatively, based on the conceptual model of partnering and alliancing in construction project management, Liang et al. [8] elaborated a set of cooperation attributes for selecting joint venture contractors in large-scale infrastructure projects, including compatible culture, contract, communication, collaboration, cooperation ability and cooperation satisfaction. To provide a deeper insights

on factors that affect contractors' cooperation under international construction joint ventures in construction projects, Hwang et al. [27] conducted a survey and reported 'sharing of project risks' as the top attractive factor and 'differences in culture and working style' as the top negative factor among others. Furthermore, aiming at finding risks that most affect contractors' cooperation within project networks, Hwang and Han [29] conducted a survey from the viewpoint of contractors and sub-contractors in Singapore construction environment; they identified ten top critical network risks, such as 'different cultural norms', 'inaccurate information delivery', 'occurrence of dispute', and 'lack of risk management knowledge.' Obviously, Hwang, et al. [27] and Hwang and Han [29] contributed a feasible way to deduce more reasonable evaluative attributes on contractor's cooperation capability; however, to our best knowledge, there is still a lack of thorough investigation on a consensus set of evaluative attributes on contractor's cooperation capability for referencing. Therefore, in the light of Liang et al. [8], Hwang, et al. [27], and Hwang and Han [29], we here take 'Cooperation management capability' as one of the main evaluative attributes to assess contractors.

To reduce the significant environmental footprint [6], internal and external factors (such as government regulations and managerial concerns) are driving the entire construction industry to enforce green practices all over the world [6]. Green practices can be considered as an outcome of strategic processes through cooperation within the nexus of contractors [75]. Therefore, it is intrinsically crucial to take into account evaluative attributes on green practices in contractor selection, especially for those nearly ever-lasting mega infrastructure construction projects. Since environmental regulations of different scales (i.e., domestic, governmental, and international [76]) have increasingly become compulsory in various industrial markets, contractors should have the capability of manage and keep track of the compliance [35]. And the widely accepted way [77] to attain the compliance capability by building environment management systems [32, 34, 78], whose most-cited components [77] comprise of ISO-14001 certification [32, 34, 36, 37], eco-labeling [31, 32, 37], environment policies [33], environment planning [33], and environmental management information system (continuous monitoring and regulatory compliance) [31, 32]. Due to the reason that environmental impacts occur at every stage of the construction cycle, Rwelamila et al. [79] strongly suggested to contractors should implement green design & procurement to improve their green practices. Construction life-cycle analysis is critical in both green design for environment [33] and pollution reduction through green procurement [31, 32, 34]. Measurements of green design for environment include tracking all material and reverse flow of a project from the retrieval of raw materials out of the environment to the disposal of the product back into the environment, generally including recycle [31], reuse [32, 33], remanufacture [32, 33], disassembly and disposal [33]. In the green procurement aspect, Tan, et al. [68] suggested to reduce environmental footprints throughout the whole construction supply chain by addressing issues such as waste reduction [32, 34], environment material substitution [31, 33], hazardous

material minimization [35], and clean technology availability [33]. Furthermore, from the stance of strategic management, Fergusson and Langford [80] pointed out environmental performance of green practices positively contributes to comprehensive competitive advantages of contractors. Environmental performance has thus been recognized as one of the indispensable evaluative attributes to contractor selection [34, 78]. Sharma and Vredenburg [81] referred to environmental performance as the environmental effects that corporation's activities have on the natural milieu. To make environmental performance more measurable, many efforts have been paid to establish effective assessing approaches, such as the approach to examination on waste flows and control on construction sites [3, 82]. As for indicators of environmental performance, according to the thorough literature review by Govindan, et al. [77], the commonly adopted ones include [32–34, 36]: solid waste, chemical waste, air emission, waste water disposal and energy. In sum, we here include 'Design & procurement', 'Compliance with green legislation', and 'Environmental performance' as three other main evaluative attributes to comprehensively assess green practices of alternative contractors.

For more clarity, based on the above literature review, we listed all eight main evaluative attributes and present their definitions/principles. And the optional subdimensions of these main attributes have been also listed in Table 1 for various comprehensive considerations according to specific nature in practical problems.

(A₁) Quotation: Project value of reviewed. The lowest tender price tends to attract a client's interest as superior to other criteria.

(A₂) Credibility: Comprehensive evaluation on trustworthiness of contractors in developmental dynamics and risks from both internal and external environments, focusing on financial soundness, health and safety, past performance, work experience, etc.

(A₃) Technical strength: Comprehensive evaluation on contractors' capability of technology and innovation that tackling forthcoming complicate tasks, generally based on quality rank, technical ability, experience and knowledge of operation team, creativity & innovation, etc.

(A₄) Resource strength: Comprehensive evaluation on contractors' competitive strength on productive resources that indispensable for construction needs, generally based on technical human resource, current workload, construction machinery & equipment, fixed assets & liquidity, etc.

(A₅) Cooperation management capacity: Comprehensive evaluation on contractors' cooperation practices with participants in projects, focusing on client/contractor relationship, organizational structure and operations, compatible culture, communication and information delivery, knowledge sharing of risk management, among others.

(A₆) Design & procurement: Comprehensive evaluation on contractors' practices that improve project's whole life value by using green design, environmental friendly materials and green production processes, which promote best practices of green construction procurement throughout the supply chain.

TABLE 1: Main evaluative attributes and their optional subdimensions for green contractor selection.

No.	Attributes	Sub-dimensions	References
A ₁	Quotation	(i) Tender price (advance payment, capital bid, routine maintenance and major repairs) [8, 18, 24]	Liang, et al. [8], Fong and Choi [24], Zavadskas, et al. [18]
A ₂	Credibility	(i) past performance [10, 18, 24] (ii) work experience [25] (iii) reputation & credit rating [10, 25–27] (iv) health & safety [10, 18, 24, 26] (v) financial stability [10, 24–26, 28]	Nieto-Morote and Ruz-Vila [10], Zavadskas, et al. [18], Hatush and Skitmore [26], Fong and Choi [24], Shen, et al. [28], Darvish, et al. [25, 27]
A ₃	Technical strength	(i) technical ability [8, 10, 18, 26, 28] (ii) experience & knowledge of operation team [10, 25] (iii) quality rank [25] (iv) creativity & innovation [25]	Liang, et al. [8], Nieto-Morote and Ruz-Vila [10], Zavadskas, et al. [18], Hatush and Skitmore [26], Shen, et al. [28], Darvish, et al. [25]
A ₄	Resource strength	(i) technical human resource [24, 27] (ii) current workload [24] (iii) construction machinery & equipment [25, 27] (iv) fixed assets & liquidity [27]	Fong and Choi [24], Darvish, et al. [25], Hwang, et al. [27]
A ₅	Cooperation management capability	(i) client/contractor relationship [10, 24, 29] (ii) organizational structure & operations [8, 28] (iii) compatible culture [8, 27] (iv) communication [8, 29] (v) knowledge sharing of risk management [27, 29] (vi) information delivery [29] (vii) contract management [8]	Liang, et al. [8], Nieto-Morote and Ruz-Vila [10], Hatush and Skitmore [26], Fong and Choi [24], Shen, et al. [28], Darvish, et al. [25], Hwang, et al. [27], Hwang and Han [29], Anvuur Aaron and Kumaraswamy Mohan [30],
A ₆	Design & Procurement	(i) recycle [31] (ii) reuse [32, 33] (iii) remanufacture [32, 33] (iv) disassembly and disposal [33] (v) waste reduction [32, 34] (vi) environment material substitution [31, 33] (vii) hazardous material minimization [35] (viii) clean technology availability [33]	Lin [35], Humphreys, et al. [34], Chiou, et al. [32], Lee, et al. [31], Humphreys, et al. [33]
A ₇	Compliance with green legislation	(i) ISO-14001 certification [32, 34, 36, 37] (ii) eco-labeling [31, 32, 37] (iii) environment policies [33] (iv) environment planning [33] (v) environmental management information system [31, 32]	Humphreys, et al. [34], Chiou, et al. [32], Yang and Wu [36], Liu and Liu [37], Lee, et al. [31], Humphreys, et al. [33]
A ₈	Environmental performance	(i) solid waste [33, 34, 36] (ii) chemical waste [33, 34, 36] (iii) air emission [33, 34, 36] (iv) waste water disposal [32–34, 36] (v) energy [33, 34]	Humphreys, et al. [34], Chiou, et al. [32], Yang and Wu [36], Humphreys, et al. [33]

(A₇) Compliance with green legislation: Comprehensive evaluation on the extent to which contractors' practices satisfy different governmental green or sustainability legislations, according to the aspects of ISO-14001 certification, eco-labeling, environment policies, environment planning, environmental management information system, etc.

(A₈) Environmental performance: Comprehensive evaluation on environmental effects that the corporation's activities have on the natural milieu. Environmental performance can commonly be measured through operative performance indicators (i.e. energy/resource utilization, emission reduction, and waste disposal).

2.2. Problem Definition. The contractor selection as well as many other multicriteria decisions impacting the overall project should be made during the front end planning stage of a project, the point at which a group of designated decision-makers have the power to accept or reject a contractor for a specific project or its work packages [5, 9]. When using MADM mechanism to cope with complicate contractor selection problems [5], normally few nominated contractors will be ready for the decision-makers to vote on. Due to complexity of the problems and limitedness of knowledge, decision-makers usually feel confident in expressing their opinions by use of interval numbers [83] or uncertain linguistic terms [52]. Although widely-accepted majority rule will quickly help the group of decision-makers arrive at a decision on an uncertain linguistic term (e.g., $[s_4, s_5]$), to which obviously there exists decision hesitancy because different opinions exist. Therefore, in this paper, we define the interval-valued dual hesitant fuzzy uncertain unbalanced linguistic set (IVDHF_UUBLS) to help the decision-making panel elicit their assessments more objectively and completely.

From another point of view, various attitudinal characters (degree of orness) commonly exist because individual expert holds specific backgrounds, and decision process that involves the attitudinal character of group decision-makers must coordinate those various attitudinal characters into one complex attitudinal character [61]. Therefore, we adopt the concept of order-inducing vector [62] to reflect group complex attitudinal character and develop a TOPSIS-based method to rationally determine the order-inducing vector. Besides, as Tan and Chen [84] pointed out, for real-world sophisticated MADM problems, the independency axiom [85] cannot generally satisfied. For example, upgrading in green performance will raise the quotation and intrinsically result in requirements for high-standard collaboration between contractors and general constructor. In viewing of this common phenomenon, we take attributes' interdependency as a third indispensable characteristic in tackling complexity in green contractor selection in mega infrastructure projects. In sum, we take three characteristics of complexity to model the practical problems of complicate green contractor selection, i.e., (i) compound structure of hesitant fuzzy linguistic assessments, (ii) group attitudinal characters, and (iii) attributes' interdependency. To produce greater clarity, Figure 1 demonstrates the conceptual MADM model for green contractor selection.

Now, we can give the symbolized description of the targeted complex green contractor problems. Given a mega infrastructure project, there are a set of alternative green contractors, i.e., $X = \{x_1, x_2, \dots, x_n\}$, for its subprojects. Let $A = \{A_1, A_2, \dots, A_m\}$ be the evaluative attributes according to which decision-makers consider each green contractor. Due to high complexity in the sophisticated problem scenarios, there exists interdependency relations among the evaluative attribute.. A panel of decision-makers $E = \{E_1, E_2, \dots, E_t\}$ have been organized to give their assessments to each alternative contractor x_i ($i = 1, \dots, n$) under every attribute A_j ($j = 1, \dots, m$). In order to reflect the complicate group assessments of all alternative contractors, the hybrid expression tool of IVDHF_UUBLS that will be detailed in Section 3 is adopted to depict the assessments more effectively and comprehensively. As a result, a specific decision matrix $R = (r_{ij})_{m \times n}$ whose elements are in the form of IVDHF_UUBLS is obtained. According to Merigó and Casanovas [61], suppose that an order-inducing vector ε for denoting group attitudinal characters has been reasonably obtained. Then, effective MADM approaches must be developed to determine the most appropriate green contractor(s).

3. Interval-Valued Dual Hesitant Fuzzy Uncertain Unbalanced Linguistic Set

As demonstrated in Figure 1, after the panel of decision-makers votes on an alternative contractor under certain attribute by use of specific uncertain unbalanced linguistic term set, the uncertain linguistic term $[s_4, s_5]$ stands out because of the majority rule while different opinions should also be included and considered in MADM processes. To that end, based on interval-valued dual hesitant fuzzy set (IVD-HFS) [47] and the unbalanced linguistic term set (ULTS) [59], we here first introduce an interval-valued dual hesitant fuzzy uncertain unbalanced linguistic set (IVDHF_UUBLS), which incorporate different opinions of decision-makers as membership degrees or nonmembership degrees to the majority-voted $[s_4, s_5]$. Then we develop operational rules as well as distance measure for the IVDHF_UUBLS. Regarding definitions of the IVDHFS and ULTS, one can refer to Appendix A.

3.1. Definition of IVDHF_UUBLS

Definition 1. Let X be a fixed set and S be a finite and continuous unbalanced linguistic label set. Then an IVDHF_UUBLS SD on X is defined as

$$SD = \{ \langle x, \tilde{s}_{\theta(x)}, \tilde{h}(x), \tilde{g}(x) \rangle \mid x \in X \}, \quad (1)$$

where $\tilde{s}_{\theta(x)} = [s_\alpha, s_\beta]$ represents judgment to object x , s_α and s_β are two unbalanced linguistic variables from predefined unbalanced linguistic label set S which represents decision-makers' judgments to an evaluated object X . $\tilde{h}(x) = \bigcup \{\tilde{\mu}\} = \bigcup_{[\mu^L, \mu^U] \in \tilde{h}(x)} \{[\mu^L, \mu^U]\}$ and $\tilde{g}(x) = \bigcup \{\tilde{\nu}\} = \bigcup_{[\nu^L, \nu^U] \in \tilde{g}(x)} \{[\nu^L, \nu^U]\}$ are two sets of closed intervals

FIGURE 1: Conceptual MADM model for tackling complexity in green contractor selection.

in $[0, 1]$. $\tilde{h}(x)$ denotes possible membership degrees that x belongs to $\tilde{s}_{\theta(x)}$, and $\tilde{g}(x)$ represents possible nonmembership degrees of x to $\tilde{s}_{\theta(x)}$. $\tilde{h}(x)$ and $\tilde{g}(x)$ hold conditions: $\tilde{\mu}, \tilde{\nu} \in [0, 1]$ and $0 \leq (\mu^U)^+ + (\nu^U)^+ \leq 1$, where $(\mu^U)^+ \in \tilde{h}^+(x) = \bigcup_{[\mu^L, \mu^U] \in \tilde{h}(x)} \max\{\mu^U\}$ and $(\nu^U)^+ \in \tilde{g}^+(x) = \bigcup_{[\nu^L, \nu^U] \in \tilde{g}(x)} \max\{\nu^U\}$ for all $x \in X$. When $X = \{x_1, x_2, \dots, x_n\}$ has only one element, SD reduces to $(\tilde{s}_{\theta}, \tilde{h}, \tilde{g})$, which is called an interval-valued dual hesitant fuzzy uncertain unbalanced linguistic (IVDHF_UUBLN) number (IVDHF_UUBLN).

3.2. Operational Rules for IVDHF_UUBLN. On the strength of operational rules for uncertain linguistic set [52], unbalanced linguistic set [59] and interval-valued dual hesitant fuzzy set [47], we get the following operations for IVDHF_UUBLN.

Definition 2. Let $sd = (\tilde{s}_{\theta}, \tilde{h}, \tilde{g}) = ([s_{\alpha}, s_{\beta}], \tilde{h}, \tilde{g})$, $sd_1 = (\tilde{s}_{\theta_1}, \tilde{h}_1, \tilde{g}_1) = ([s_{\alpha_1}, s_{\beta_1}], \tilde{h}_1, \tilde{g}_1)$ and $sd_2 = (\tilde{s}_{\theta_2}, \tilde{h}_2, \tilde{g}_2) = ([s_{\alpha_2}, s_{\beta_2}], \tilde{h}_2, \tilde{g}_2)$ be any three IVDHF_UUBLNs, $\lambda \in [0, 1]$, operations on these IVDHF_UUBLNs are defined as:

$$\begin{aligned}
 (1) \quad \lambda sd &= \bigcup_{(\tilde{s}_{\theta}, \tilde{h}, \tilde{g}) \in sd} \left(\left[s_{\lambda \Delta_{t_0}^{-1}(TF_{t_0}^{t_{k_1}}(\psi(s_{\alpha})))}, s_{\lambda \Delta_{t_0}^{-1}(TF_{t_0}^{t_{k_2}}(\psi(s_{\beta})))} \right], \right. \\
 &\quad \left. \bigcup_{[\mu^L, \mu^U] \in \tilde{h}, [\nu^L, \nu^U] \in \tilde{g}} \left\{ \left\{ \left[1 - (1 - \mu^L)^{\lambda}, 1 - (1 - \mu^U)^{\lambda} \right] \right\}, \left\{ \left[(\nu^L)^{\lambda}, (\nu^U)^{\lambda} \right] \right\} \right\} \right); \\
 (2) \quad sd^{\lambda} &= \bigcup_{(\tilde{s}_{\theta}, \tilde{h}, \tilde{g}) \in sd} \left(\left[s_{(\Delta_{t_0}^{-1}(TF_{t_0}^{t_{k_1}}(\psi(s_{\alpha})))^{\lambda})}, s_{(\Delta_{t_0}^{-1}(TF_{t_0}^{t_{k_2}}(\psi(s_{\beta})))^{\lambda})} \right] \right. \\
 &\quad \left. \bigcup_{[\mu^L, \mu^U] \in \tilde{h}, [\nu^L, \nu^U] \in \tilde{g}} \left\{ \left\{ \left[(\mu^L)^{\lambda}, (\mu^U)^{\lambda} \right] \right\}, \left\{ \left[1 - (1 - \nu^L)^{\lambda}, 1 - (1 - \nu^U)^{\lambda} \right] \right\} \right\} \right); \\
 (3) \quad sd_1 \oplus sd_2 &= \bigcup_{(\tilde{s}_{\theta_1}, \tilde{h}_1, \tilde{g}_1) \in sd_1, (\tilde{s}_{\theta_2}, \tilde{h}_2, \tilde{g}_2) \in sd_2} \left(\left[s_{\Delta_{t_0}^{-1}(TF_{t_0}^{t_{i_1}}(\psi(s_{\alpha_1}))) + \Delta_{t_0}^{-1}(TF_{t_0}^{t_{j_1}}(\psi(s_{\alpha_2})))}, s_{\Delta_{t_0}^{-1}(TF_{t_0}^{t_{i_2}}(\psi(s_{\beta_1}))) + \Delta_{t_0}^{-1}(TF_{t_0}^{t_{j_2}}(\psi(s_{\beta_2})))} \right], \right. \\
 &\quad \left. \bigcup_{[\mu_1^L, \mu_1^U] \in \tilde{h}_1, [\mu_2^L, \mu_2^U] \in \tilde{h}_2, [\nu_1^L, \nu_1^U] \in \tilde{g}_1, [\nu_2^L, \nu_2^U] \in \tilde{g}_2} \left\{ \left\{ \left[\mu_1^L + \mu_2^L - \mu_1^L \mu_2^L, \mu_1^U + \mu_2^U - \mu_1^U \mu_2^U \right] \right\}, \left\{ \left[\nu_1^L \nu_2^L, \nu_1^U \nu_2^U \right] \right\} \right\} \right); \\
 (4) \quad sd_1 \otimes sd_2 &= \bigcup_{(\tilde{s}_{\theta_1}, \tilde{h}_1, \tilde{g}_1) \in sd_1, (\tilde{s}_{\theta_2}, \tilde{h}_2, \tilde{g}_2) \in sd_2} \left(\left[s_{\Delta_{t_0}^{-1}(TF_{t_0}^{t_{i_1}}(\psi(s_{\alpha_1}))) \times \Delta_{t_0}^{-1}(TF_{t_0}^{t_{j_1}}(\psi(s_{\alpha_2})))}, s_{\Delta_{t_0}^{-1}(TF_{t_0}^{t_{i_2}}(\psi(s_{\beta_1}))) \times \Delta_{t_0}^{-1}(TF_{t_0}^{t_{j_2}}(\psi(s_{\beta_2})))} \right], \right. \\
 &\quad \left. \bigcup_{[\mu_1^L, \mu_1^U] \in \tilde{h}_1, [\mu_2^L, \mu_2^U] \in \tilde{h}_2, [\nu_1^L, \nu_1^U] \in \tilde{g}_1, [\nu_2^L, \nu_2^U] \in \tilde{g}_2} \left\{ \left\{ \left[\mu_1^L \mu_2^L, \mu_1^U \mu_2^U \right] \right\}, \left\{ \left[\nu_1^L + \nu_2^L - \nu_1^L \nu_2^L, \nu_1^U + \nu_2^U - \nu_1^U \nu_2^U \right] \right\} \right\} \right).
 \end{aligned} \tag{2}$$

In above, details about the transformation functions of TF and Δ , linguistic hierarchies (LH) as well as the transformation procedures for unbalanced linguistic term sets are shown in Appendix A.

Theorem 3. Letting $sd = (\tilde{s}_g, \tilde{h}, \tilde{g})$, $sd_1 = (\tilde{s}_{g_1}, \tilde{h}_1, \tilde{g}_1)$, and $sd_2 = (\tilde{s}_{g_2}, \tilde{h}_2, \tilde{g}_2)$ be any three IVDHF_UUBLNs, $\lambda, \lambda_1, \lambda_2 \in [0, 1]$, then following properties are true:

- (1) $sd_1 \oplus sd_2 = sd_2 \oplus sd_1$; (2) $sd_1 \otimes sd_2 = sd_2 \otimes sd_1$; (3) $\lambda(sd_1 \oplus sd_2) = \lambda sd_1 \oplus \lambda sd_2$;
 (4) $sd_1^{\lambda} \otimes sd_2^{\lambda} = (sd_1 \otimes sd_2)^{\lambda}$; (5) $\lambda_1 sd \oplus \lambda_2 sd = (\lambda_1 + \lambda_2)sd$; (6) $sd^{\lambda_1} \otimes sd^{\lambda_2} = sd^{\lambda_1 + \lambda_2}$.

Proof. Omitted $\square$

In Definition 2 and Theorem 3, $t_{k_1}, t_{k_2}, t_{i_1}, t_{i_2}, t_{j_1}$, and t_{j_2} are corresponding levels of $s_{\alpha}, s_{\beta}, s_{\alpha_1}, s_{\beta_1}, s_{\alpha_2}$, and s_{α_2} in LH , respectively. t_0 is the maximum level of $s_{\alpha}, s_{\beta}, s_{\alpha_1}, s_{\beta_1}, s_{\alpha_2}$, and s_{α_2} in LH . Furthermore, to compare any two IVDHF_UUBLNs, we also have following definitions.

Definition 4. Let $sd = (\tilde{s}_g, \tilde{h}, \tilde{g})$ be an IVDHF_UUBLN, $\tilde{s}_g = [s_{\alpha}, s_{\beta}]$; then score function $S(sd)$ and accuracy function $P(sd)$ can be represented by

$$S(sd) = \frac{\Delta_{t_0}^{-1}(TF_{t_0}^{t_{k_1}}(\psi(s_{\alpha}))) + \Delta_{t_0}^{-1}(TF_{t_0}^{t_{k_2}}(\psi(s_{\beta})))}{2} \times \frac{1}{2} \left(\frac{1}{l(\tilde{h})} \sum_{[\mu^L, \mu^U] \in \tilde{h}} \mu^L - \frac{1}{l(\tilde{g})} \sum_{[\nu^L, \nu^U] \in \tilde{g}} \nu^L \right. \quad (3)$$

$$\left. + \frac{1}{l(\tilde{h})} \sum_{[\mu^L, \mu^U] \in \tilde{h}} \mu^U - \frac{1}{l(\tilde{g})} \sum_{[\nu^L, \nu^U] \in \tilde{g}} \nu^U \right)$$

$P(sd)$

$$= \frac{\Delta_{t_0}^{-1}(TF_{t_0}^{t_{k_1}}(\psi(s_{\alpha}))) + \Delta_{t_0}^{-1}(TF_{t_0}^{t_{k_2}}(\psi(s_{\beta})))}{2}$$

$$\times \frac{1}{2} \left(\frac{1}{l(\tilde{h})} \sum_{[\mu^L, \mu^U] \in \tilde{h}} \mu^L + \frac{1}{l(\tilde{g})} \sum_{[\nu^L, \nu^U] \in \tilde{g}} \nu^L \right. \quad (4)$$

$$\left. + \frac{1}{l(\tilde{h})} \sum_{[\mu^L, \mu^U] \in \tilde{h}} \mu^U + \frac{1}{l(\tilde{g})} \sum_{[\nu^L, \nu^U] \in \tilde{g}} \nu^U \right)$$

where $l(\tilde{h})$ and $l(\tilde{g})$ are numbers of values in $\tilde{h}$ and $\tilde{g}$, respectively, t_{k_1} and t_{k_2} are the corresponding levels of s_{α} and s_{β} in LH , and t_0 is the maximum level of t_k in LH .

Definition 5. Given any IVDHF_UUBLNs $sd_1 = (\tilde{s}_{g_1}, \tilde{h}_1, \tilde{g}_1)$, $sd_2 = (\tilde{s}_{g_2}, \tilde{h}_2, \tilde{g}_2)$, then

- (1) If $S(sd_1) < S(sd_2)$, then $sd_1 < sd_2$.
 (2) If $S(sd_1) = S(sd_2)$, then

- (a) If $P(sd_1) = P(sd_2)$, then $sd_1 = sd_2$;
 (b) If $P(sd_1) < P(sd_2)$, then $sd_1 < sd_2$.

3.3. Distance Measure for IVDHF_UUBLNs. When $l(\tilde{h})$ or $l(\tilde{g})$ of two IVDHF_UUBLNs are unequal, the complementing method [86] is normally adopted to design distance measures. Note that artificially adding values to shorter ones in the complementing method will cause information distortion. To avoid this limitation, we provide the following distance measure.

Definition 6. Let two IVDHF_UUBLNs $sd_1 = (\tilde{s}_{g_1}, \tilde{h}_1, \tilde{g}_1)$ and $sd_2 = (\tilde{s}_{g_2}, \tilde{h}_2, \tilde{g}_2)$, where $\tilde{s}_{g_1} = [s_{\alpha_1}, s_{\beta_1}]$, $\tilde{s}_{g_2} = [s_{\alpha_2}, s_{\beta_2}]$. $l_{\tilde{h}_1}, l_{\tilde{h}_2}, l_{\tilde{g}_1}$ and $l_{\tilde{g}_2}$ are lengths of $\tilde{h}_1, \tilde{h}_2, \tilde{g}_1$, and $\tilde{g}_2$, respectively, denoting number of elements in $\tilde{h}_1, \tilde{h}_2, \tilde{g}_1$, and $\tilde{g}_2$. Suppose $I_1 = (1/(n(t_{i_1}) - 1))\Delta_{t_0}^{-1}(TF_{t_0}^{t_{i_1}}(\psi(s_{\alpha_1})))$, $I_2 = (1/(n(t_{i_2}) - 1))\Delta_{t_0}^{-1}(TF_{t_0}^{t_{i_2}}(\psi(s_{\beta_1})))$, $I_3 = (1/(n(t_{j_1}) - 1))\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j_1}}(\psi(s_{\alpha_2})))$, $I_4 = (1/(n(t_{j_2}) - 1))\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j_2}}(\psi(s_{\beta_2})))$, where $t_{i_1}, t_{i_2}, t_{j_1}$, and t_{j_2} are the corresponding levels of unbalanced linguistic terms $s_{\alpha_1}, s_{\beta_1}, s_{\alpha_2}$, and s_{β_2} in the linguistic hierarchy LH and t_0 is the maximum level of $s_{\alpha_1}, s_{\beta_1}, s_{\alpha_2}$, and s_{β_2} in LH . Then by use of normalized Euclidean distance, we define a distance measure d for IVDHF_UUBLNs as follows.

Situation 7. When $l_{\tilde{h}_1} = l_{\tilde{h}_2} = l_1$ and $l_{\tilde{g}_1} = l_{\tilde{g}_2} = l_2$, then

$$d(sd_1, sd_2) = \left(\frac{1}{2} \left(\frac{1}{l_1} \cdot \sum_{k=1}^{l_1} \left(\left| I_1 \mu_{\tilde{h}_1}^{L_j} - I_3 \mu_{\tilde{h}_2}^{L_k} \right|^2 + \left| I_2 \mu_{\tilde{h}_1}^{U_j} - I_4 \mu_{\tilde{h}_2}^{U_k} \right|^2 \right) + \frac{1}{l_2} \cdot \sum_{k=1}^{l_2} \left(\left| I_1 \nu_{\tilde{g}_1}^{L_j} - I_3 \nu_{\tilde{g}_2}^{L_k} \right|^2 + \left| I_2 \nu_{\tilde{g}_1}^{U_j} - I_4 \nu_{\tilde{g}_2}^{U_k} \right|^2 \right) \right) \right)^{1/2} \quad (5)$$

Situation 8. When $l_{\tilde{h}_1} \neq l_{\tilde{h}_2}$ or $l_{\tilde{g}_1} \neq l_{\tilde{g}_2}$, then

$$d(sd_1, sd_2) = \left(\frac{1}{2} \left(\frac{1}{l_{\tilde{h}_1} l_{\tilde{h}_2}} \cdot \sum_{j=1}^{l_{\tilde{h}_1}} \sum_{k=1}^{l_{\tilde{h}_2}} \left(\left| I_1 \mu_{\tilde{h}_1}^{L_j} - I_3 \mu_{\tilde{h}_2}^{L_k} \right|^2 + \left| I_2 \mu_{\tilde{h}_1}^{U_j} - I_4 \mu_{\tilde{h}_2}^{U_k} \right|^2 \right) + \frac{1}{l_{\tilde{g}_1} l_{\tilde{g}_2}} \cdot \sum_{j=1}^{l_{\tilde{g}_1}} \sum_{k=1}^{l_{\tilde{g}_2}} \left(\left| I_1 \nu_{\tilde{g}_1}^{L_j} - I_3 \nu_{\tilde{g}_2}^{L_k} \right|^2 + \left| I_2 \nu_{\tilde{g}_1}^{U_j} - I_4 \nu_{\tilde{g}_2}^{U_k} \right|^2 \right) \right) \right)^{1/2} \quad (6)$$

Theorem 9. The distance measure d defined in Definition 6 satisfies following properties:

- (1) $0 \leq d(sd_1, sd_2) \leq 1$;

- (2) $d(sd_1, sd_2) = 0$ if and only if sd_1 and sd_2 are perfectly consistent;
- (3) $d(sd_1, sd_2) = d(sd_2, sd_1)$.

4. Generalized Aggregation Operators for IVDHF_UUBLs

4.1. *Definitions of Operators.* Based on the generalized operators firstly introduced by Yager [87], we here develop some

fundamental generalized aggregation operators for the newly defined IVDHF_UUBLs.

Definition 10. Given a collection of IVDHF_UUBLNs $sd_j (j = 1, \dots, n)$, their weighting vector $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T, \omega_j \in [0, 1], \sum_{j=1}^n \omega_j = 1$. λ be a parameter, $\lambda \in (0, +\infty)$.

(1) *Generalized IVDHFUUBL Weighted Average (GIVDHFUUBLWA) Operator*

$$\begin{aligned}
 GIVDHFUUBLWA_{\omega, \lambda}(sd_1, sd_2, \dots, sd_n) &= \left(\bigoplus_{j=1}^n (\omega_j sd_j^\lambda) \right)^{1/\lambda} \\
 &= \bigcup_{(\tilde{s}_{\theta_j}, \tilde{h}_j, \tilde{g}_j) \in sd_j} \left(\left[S_{(\sum_{j=1}^n \omega_j (\Delta_{i_0}^{-1}(TF_{i_0}^{t_{j1}}(\psi(s_{\alpha_j}))))^\lambda)^{1/\lambda}}, S_{(\sum_{j=1}^n \omega_j (\Delta_{i_0}^{-1}(TF_{i_0}^{t_{j2}}(\psi(s_{\beta_j}))))^\lambda)^{1/\lambda}} \right], \right. \\
 &\quad \bigcup_{[\mu_j^L, \mu_j^U] \in \tilde{h}_j, [\nu_j^L, \nu_j^U] \in \tilde{g}_j} \left\{ \left[\left(1 - \prod_{j=1}^n \left(1 - (\mu_j^L)^\lambda \right)^{\omega_j} \right)^{1/\lambda}, \left(1 - \prod_{j=1}^n \left(1 - (\mu_j^U)^\lambda \right)^{\omega_j} \right)^{1/\lambda} \right] \right\}, \\
 &\quad \left. \left\{ \left[1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \nu_j^L)^\lambda \right)^{\omega_j} \right)^{1/\lambda}, 1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \nu_j^U)^\lambda \right)^{\omega_j} \right)^{1/\lambda} \right] \right\} \right\} \right). \tag{7}
 \end{aligned}$$

(2) *Generalized IVDHFUUBL Weighted Geometric (GIVDHFUUBLWG) Operator*

$$\begin{aligned}
 GIVDHFUUBLWG_{\omega, \lambda}(sd_1, sd_2, \dots, sd_n) &= \frac{1}{\lambda} \left(\bigotimes_{j=1}^n (\lambda sd_j)^{\omega_j} \right) \\
 &= \bigcup_{(\tilde{s}_{\theta_j}, \tilde{h}_j, \tilde{g}_j) \in sd_j} \left(\left[S_{(1/\lambda) \prod_{j=1}^n (\lambda \Delta_{i_0}^{-1}(TF_{i_0}^{t_{j1}}(\psi(s_{\alpha_j}))))^{\omega_j}}, S_{(1/\lambda) \prod_{j=1}^n (\lambda \Delta_{i_0}^{-1}(TF_{i_0}^{t_{j2}}(\psi(s_{\beta_j}))))^{\omega_j}} \right], \right. \\
 &\quad \bigcup_{[\mu_j^L, \mu_j^U] \in \tilde{h}_j, [\nu_j^L, \nu_j^U] \in \tilde{g}_j} \left\{ \left[1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \mu_j^L)^\lambda \right)^{\omega_j} \right)^{1/\lambda}, 1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \mu_j^U)^\lambda \right)^{\omega_j} \right)^{1/\lambda} \right] \right\}, \\
 &\quad \left. \left\{ \left[\left(1 - \prod_{j=1}^n \left(1 - (\nu_j^L)^\lambda \right)^{\omega_j} \right)^{1/\lambda}, \left(1 - \prod_{j=1}^n \left(1 - (\nu_j^U)^\lambda \right)^{\omega_j} \right)^{1/\lambda} \right] \right\} \right\} \right). \tag{8}
 \end{aligned}$$

Definition 11. For a collection of IVDHF_UUBLNs $sd_j (j = 1, \dots, n)$, $sd_{\sigma(j)}$ be the j th largest, $w = (w_1, w_2, \dots, w_n)^T$ be the

aggregation-associated weighting vector, $w_j \in [0, 1], \sum_{j=1}^n w_j = 1$, λ is a parameter such that $\lambda \in (0, +\infty)$, $S^n \rightarrow S$. Then,

(1) Generalized IVDHFUUBL Ordered Weighted Average
(GIVDHFUUBLOWA) Operator

$$\begin{aligned}
 \text{GIVDHFUUBLOWA}_{\omega, \lambda}(sd_1, sd_2, \dots, sd_n) &= \left(\bigoplus_{j=1}^n (w_j sd_{\sigma(j)})^\lambda \right)^{1/\lambda} \\
 &= \bigcup_{(\bar{s}_{\sigma(j)}, \bar{h}_{\sigma(j)}, \bar{g}_{\sigma(j)}) \in \bar{sd}_{\sigma(j)}} \left(\left[S_{\sum_{j=1}^n w_j (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j1}}(\psi(s_{\alpha_{\sigma(j)}})))^\lambda)^{1/\lambda}}, S_{\sum_{j=1}^n w_j (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j2}}(\psi(s_{\beta_{\sigma(j)}})))^\lambda)^{1/\lambda}} \right], \right. \\
 &\quad \bigcup_{[\mu_{\sigma(j)}^L, \mu_{\sigma(j)}^U] \in \bar{h}_{\sigma(j)}, [\nu_{\sigma(j)}^L, \nu_{\sigma(j)}^U] \in \bar{g}_{\sigma(j)}} \left\{ \left[\left(1 - \prod_{j=1}^n \left(1 - (\mu_{\sigma(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, \left(1 - \prod_{j=1}^n \left(1 - (\mu_{\sigma(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\}, \\
 &\quad \left. \left\{ \left[1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \nu_{\sigma(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, 1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \nu_{\sigma(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\} \right\} \right); \tag{9}
 \end{aligned}$$

(2) Generalized IVDHFUUBL Ordered Weighted Geometric
(GIVDHFUUBLOWG) Operator

$$\begin{aligned}
 \text{GIVDHFUUBLOWG}_{w, \lambda}(sd_1, sd_2, \dots, sd_n) &= \frac{1}{\lambda} \left(\bigotimes_{j=1}^n (\lambda sd_{\sigma(j)})^{w_j} \right) \\
 &= \bigcup_{(\bar{s}_{\sigma(j)}, \bar{h}_{\sigma(j)}, \bar{g}_{\sigma(j)}) \in \bar{sd}_{\sigma(j)}} \left(\left[S_{(1/\lambda) \prod_{j=1}^n (\lambda \Delta_{t_0}^{-1}(TF_{t_0}^{t_{j1}}(\psi(s_{\alpha_{\sigma(j)}})))^{w_j}}, S_{(1/\lambda) \prod_{j=1}^n (\lambda \Delta_{t_0}^{-1}(TF_{t_0}^{t_{j2}}(\psi(s_{\beta_{\sigma(j)}})))^{w_j}} \right], \right. \\
 &\quad \bigcup_{[\mu_{\sigma(j)}^L, \mu_{\sigma(j)}^U] \in \bar{h}_{\sigma(j)}, [\nu_{\sigma(j)}^L, \nu_{\sigma(j)}^U] \in \bar{g}_{\sigma(j)}} \left\{ \left[\left(1 - \prod_{j=1}^n \left(1 - (1 - \mu_{\sigma(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, 1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \mu_{\sigma(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\}, \\
 &\quad \left. \left\{ \left[\left(1 - \prod_{j=1}^n \left(1 - (1 - \nu_{\sigma(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, \left(1 - \prod_{j=1}^n \left(1 - (1 - \nu_{\sigma(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\} \right\} \right); \tag{10}
 \end{aligned}$$

Definition 12. For a collection of IVDHF-UUBLNs $sd_j (j = 1, \dots, n)$, $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$ is the weighting vector, $\omega_j \in [0, 1]$, $\sum_{j=1}^n \omega_j = 1$. n is a balancing coefficient. $w = (w_1, w_2, \dots, w_n)^T$ is the aggregation-associated weighting vector with $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$.

(1) Generalized IVDHFUUBL Hybrid Average (GIVDHFU-
UBLHA) Operator

$$\begin{aligned}
 \text{GIVDHFUUBLHA}_{\omega, w, \lambda}(sd_1, sd_2, \dots, sd_n) &= \left(\bigoplus_{j=1}^n (w_j \bar{sd}_{\sigma(j)})^\lambda \right)^{1/\lambda} \\
 &= \bigcup_{(\bar{s}_{\sigma(j)}, \bar{h}_{\sigma(j)}, \bar{g}_{\sigma(j)}) \in \bar{sd}_{\sigma(j)}} \left(\left[\bar{S}_{\sum_{j=1}^n w_j (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j1}}(\psi(\bar{s}_{\alpha_{\sigma(j)}})))^\lambda)^{1/\lambda}}, \bar{S}_{\sum_{j=1}^n w_j (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j2}}(\psi(\bar{s}_{\beta_{\sigma(j)}})))^\lambda)^{1/\lambda}} \right], \right.
 \end{aligned}$$

$$\bigcup_{[\bar{\mu}_{\sigma(j)}^L, \bar{\mu}_{\sigma(j)}^U] \in \bar{h}_{\sigma(j)}, [\bar{\nu}_{\sigma(j)}^L, \bar{\nu}_{\sigma(j)}^U] \in \bar{g}_{\sigma(j)}} \left\{ \left[\left[\left(1 - \prod_{j=1}^n \left(1 - (\bar{\mu}_{\sigma(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, \left(1 - \prod_{j=1}^n \left(1 - (\bar{\mu}_{\sigma(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\}, \right. \\ \left. \left\{ \left[1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \bar{\nu}_{\sigma(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, 1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \bar{\nu}_{\sigma(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\} \right\} \right\}, \quad (11)$$

where $\bar{s}d_{\sigma(j)}$ is the j th largest and

$$\bar{s}d_j = n\omega_j s d_j = \bigcup_{(\bar{s}_{\theta_j}, \bar{h}_j, \bar{g}_j) \in s d_j} \left(\left[s_{n\omega_j(\Delta_{i_0}^{-1}(TF_{i_0}^{t_{j1}}(\psi(s_{\alpha_j}))))}, s_{n\omega_j(\Delta_{i_0}^{-1}(TF_{i_0}^{t_{j2}}(\psi(s_{\beta_j}))))} \right], \right. \\ \left. \bigcup_{[\mu_j^L, \mu_j^U] \in \bar{h}_j, [\nu_j^L, \nu_j^U] \in \bar{g}_j} \left\{ \left[1 - (1 - \mu_j^L)^{n\omega_j}, 1 - (1 - \mu_j^U)^{n\omega_j} \right] \right\}, \left\{ \left[(\nu_j^L)^{n\omega_j}, (\nu_j^U)^{n\omega_j} \right] \right\} \right\} \right). \quad (12)$$

(2) Generalized IVDHFUUBL Hybrid Geometric (GIVDHFUUBLHG) Operator

$$GIVDHFUUBLHG_{\omega, \omega, \lambda}(s d_1, s d_2, \dots, s d_n) = \frac{1}{\lambda} \left(\bigotimes_{j=1}^n (\lambda \bar{\bar{s}d}_{\sigma(j)})^{w_j} \right) \\ = \bigcup_{(\bar{s}_{\theta_{\sigma(j)}}, \bar{h}_{\sigma(j)}, \bar{g}_{\sigma(j)}) \in \bar{\bar{s}d}_{\sigma(j)}} \left(\left[\hat{s}_{(1/\lambda) \prod_{j=1}^n (\lambda \Delta_{i_0}^{-1}(TF_{i_0}^{t_{j1}}(\psi(\bar{s}_{\theta_{\sigma(j)}}))))}^{w_j}, \hat{s}_{(1/\lambda) \prod_{j=1}^n (\lambda \Delta_{i_0}^{-1}(TF_{i_0}^{t_{j2}}(\psi(\bar{s}_{\theta_{\sigma(j)}}))))}^{w_j} \right], \right. \\ \bigcup_{[\bar{\mu}_{\sigma(j)}^L, \bar{\mu}_{\sigma(j)}^U] \in \bar{\hat{h}}_{\sigma(j)}, [\bar{\nu}_{\sigma(j)}^L, \bar{\nu}_{\sigma(j)}^U] \in \bar{\hat{g}}_{\sigma(j)}} \left\{ \left[\left[1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \bar{\mu}_{\sigma(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, 1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \bar{\mu}_{\sigma(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\}, \right. \\ \left. \left\{ \left[\left(1 - \prod_{j=1}^n \left(1 - (\bar{\nu}_{\sigma(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, \left(1 - \prod_{j=1}^n \left(1 - (\bar{\nu}_{\sigma(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\} \right\} \right), \quad (13)$$

where $\bar{\bar{s}d}_{\sigma(j)}$ is the j th largest and

$$\bar{\bar{s}d}_j = s d_j^{n\omega_j} = \bigcup_{(\bar{s}_{\theta_j}, \bar{h}_j, \bar{g}_j) \in s d_j} \left(\left[s_{(\Delta_{i_0}^{-1}(TF_{i_0}^{t_{j1}}(\psi(s_{\alpha_j}))))}^{n\omega_j}, s_{(\Delta_{i_0}^{-1}(TF_{i_0}^{t_{j2}}(\psi(s_{\beta_j}))))}^{n\omega_j} \right], \right. \\ \left. \bigcup_{[\mu_j^L, \mu_j^U] \in \bar{h}_j, [\nu_j^L, \nu_j^U] \in \bar{g}_j} \left\{ \left[(\mu_j^L)^{n\omega_j}, (\mu_j^U)^{n\omega_j} \right] \right\}, \left\{ \left[1 - (1 - \nu_j^L)^{n\omega_j}, 1 - (1 - \nu_j^U)^{n\omega_j} \right] \right\} \right\} \right). \quad (14)$$

When confronted with ill-structured situations where decision-maker's complex attitudinal characters need to be included, order-inducing vectors provide an effective way [88–90]. Thus, we further define following induced operators for IVDHF_UUBLNs.

Definition 13. For a collection of IVDHF_UUBLNs sd_j ($j = 1, \dots, n$), $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$ is the weighting vector,

$\omega_j \in [0, 1]$, $\sum_{j=1}^n \omega_j = 1$. n is a balancing coefficient. $w = (w_1, w_2, \dots, w_n)^T$ is the aggregation-associated weighting vector, $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$. ε_j denote a set of order inducing vectors.

(1) *Induced Generalized IVDHFUUBL Hybrid Average (I-GIVDHFUUBLHA) Operator*

$$\begin{aligned}
 I\text{-GIVDHFUUBLHA}_{\omega, w, \lambda}(< \varepsilon_1, sd_1 >, < \varepsilon_2, sd_2 >, \dots, < \varepsilon_n, sd_n >) &= \left(\bigoplus_{j=1}^n (w_j \overline{sd}_{\pi(j)}^\lambda) \right)^{1/\lambda} \\
 &= \bigcup_{(\bar{s}_{\theta_{\pi(j)}}, \bar{\mu}_{\pi(j)}^L, \bar{\mu}_{\pi(j)}^U, \bar{v}_{\pi(j)}^L, \bar{v}_{\pi(j)}^U) \in \overline{sd}_{\pi(j)}} \left(\left[\bar{s}_{\left(\sum_{j=1}^n w_j (\Delta_{\varepsilon_1}^{-1}(TF_{\varepsilon_1}^{t_{j1}}(\psi(\bar{s}_{\alpha_{\pi(j)}}))) \right))^\lambda} \right]^{1/\lambda}, \bar{s}_{\left(\sum_{j=1}^n w_j (\Delta_{\varepsilon_2}^{-1}(TF_{\varepsilon_2}^{t_{j2}}(\psi(\bar{s}_{\beta_{\pi(j)}}))) \right))^\lambda} \right]^{1/\lambda} \right), \\
 &\quad \bigcup_{(\bar{\mu}_{\pi(j)}^L, \bar{\mu}_{\pi(j)}^U, \bar{v}_{\pi(j)}^L, \bar{v}_{\pi(j)}^U) \in \bar{g}_{\pi(j)}} \left\{ \left[\left[\left(1 - \prod_{j=1}^n \left(1 - (\bar{\mu}_{\pi(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, \left(1 - \prod_{j=1}^n \left(1 - (\bar{\mu}_{\pi(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\}, \right. \\
 &\quad \left. \left\{ \left[1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \bar{v}_{\pi(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, 1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \bar{v}_{\pi(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\} \right\} \right),
 \end{aligned} \tag{15}$$

where $(\overline{sd}_{\pi(1)}, \overline{sd}_{\pi(2)}, \dots, \overline{sd}_{\pi(n)})$ is decreasing order of $(\overline{sd}_1, \overline{sd}_2, \dots, \overline{sd}_n)$ according to the order inducing vector ε_j , and

$$\begin{aligned}
 \overline{sd}_j = n\omega_j sd_j &= \bigcup_{(\bar{s}_{\theta_j}, \bar{\mu}_j^L, \bar{\mu}_j^U) \in sd_j} \left(\left[s_{n\omega_j (\Delta_{\varepsilon_1}^{-1}(TF_{\varepsilon_1}^{t_{j1}}(\psi(s_{\alpha_j}))))}, s_{n\omega_j (\Delta_{\varepsilon_2}^{-1}(TF_{\varepsilon_2}^{t_{j2}}(\psi(s_{\beta_j}))))} \right] \right), \\
 &\quad \bigcup_{(\mu_j^L, \mu_j^U) \in \bar{h}_j, (v_j^L, v_j^U) \in \bar{g}_j} \left\{ \left\{ \left[1 - (1 - \mu_j^L)^{n\omega_j}, 1 - (1 - \mu_j^U)^{n\omega_j} \right] \right\}, \left\{ \left[(v_j^L)^{n\omega_j}, (v_j^U)^{n\omega_j} \right] \right\} \right\}.
 \end{aligned} \tag{16}$$

(2) *Induced Generalized IVDHFUUBL Hybrid Geometric (I-GIVDHFUUBLHG) Operator*

$$\begin{aligned}
 I\text{-GIVDHFUUBLHG}_{\omega, w, \lambda}(< \varepsilon_1, sd_1 >, < \varepsilon_2, sd_2 >, \dots, < \varepsilon_n, sd_n >) &= \frac{1}{\lambda} \left(\bigotimes_{j=1}^n (\lambda \overline{sd}_{\pi(j)})^{w_j} \right) \\
 &= \bigcup_{(\bar{s}_{\theta_{\pi(j)}}, \bar{\mu}_{\pi(j)}^L, \bar{\mu}_{\pi(j)}^U, \bar{v}_{\pi(j)}^L, \bar{v}_{\pi(j)}^U) \in \overline{sd}_{\pi(j)}} \left(\left[\hat{s}_{(1/\lambda) \prod_{j=1}^n (\lambda \Delta_{\varepsilon_1}^{-1}(TF_{\varepsilon_1}^{t_{j1}}(\psi(\bar{s}_{\alpha_{\pi(j)}})))^{w_j}}, \hat{s}_{(1/\lambda) \prod_{j=1}^n (\lambda \Delta_{\varepsilon_2}^{-1}(TF_{\varepsilon_2}^{t_{j2}}(\psi(\bar{s}_{\beta_{\pi(j)}})))^{w_j}} \right] \right), \\
 &\quad \bigcup_{(\bar{\mu}_{\pi(j)}^L, \bar{\mu}_{\pi(j)}^U, \bar{v}_{\pi(j)}^L, \bar{v}_{\pi(j)}^U) \in \bar{g}_{\pi(j)}} \left\{ \left[\left[1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \bar{\mu}_{\pi(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, 1 - \left(1 - \prod_{j=1}^n \left(1 - (1 - \bar{\mu}_{\pi(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\}, \right. \\
 &\quad \left. \left\{ \left[\left(1 - \prod_{j=1}^n \left(1 - (\bar{v}_{\pi(j)}^L)^\lambda \right)^{w_j} \right)^{1/\lambda}, \left(1 - \prod_{j=1}^n \left(1 - (\bar{v}_{\pi(j)}^U)^\lambda \right)^{w_j} \right)^{1/\lambda} \right] \right\} \right\}
 \end{aligned} \tag{17}$$

FIGURE 2

where $(\bar{sd}_{\pi(1)}, \bar{sd}_{\pi(2)}, \dots, \bar{sd}_{\pi(n)})$ is decreasing order of $(\bar{sd}_1, \bar{sd}_2, \dots, \bar{sd}_n)$ according to the order inducing variables ε_j and

$$\bar{sd}_j = sd_j^{n\omega_j} = \bigcup_{(\bar{s}_{\theta_j}, \bar{h}_j, \bar{g}_j) \in sd_j} \left(\left[S_{(\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j1}}(\psi(s_{\alpha_j}))))^{n\omega_j}}, S_{(\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j2}}(\psi(s_{\beta_j}))))^{n\omega_j}} \right], \right. \\ \left. \bigcup_{[\mu_j^L, \mu_j^U] \in \bar{h}_j, [\nu_j^L, \nu_j^U] \in \bar{g}_j} \{[(\mu_j^L)^{n\omega_j}, (\mu_j^U)^{n\omega_j}], [1 - (1 - \nu_j^L)^{n\omega_j}, 1 - (1 - \nu_j^U)^{n\omega_j}]\} \right). \quad (18)$$

4.2. Properties of the Proposed Generalized Aggregation Operators

Theorem 14. With special values of λ , w and ω , the operators GIVDHFUUBLHA and GIVDHFUUBLHG can include a series of traditional aggregation operators as special cases and their relationship can be depicted in Figure 2.

Proof. See Appendix B. $\square$

As for the induced hybrid aggregation operators, we also have following theorem.

Theorem 15. If $(\bar{sd}_{\pi(1)}, \bar{sd}_{\pi(2)}, \dots, \bar{sd}_{\pi(n)}) = (\bar{sd}_{\sigma(1)}, \bar{sd}_{\sigma(2)}, \dots, \bar{sd}_{\sigma(n)})$, I-GIVDHFUUBLHA reduces to GIVDHFUUBLHA; If $(\bar{sd}_{\pi(1)}, \bar{sd}_{\pi(2)}, \dots, \bar{sd}_{\pi(n)}) = (\bar{sd}_{\sigma(1)}, \bar{sd}_{\sigma(2)}, \dots, \bar{sd}_{\sigma(n)})$, then I-GIVDHFUUBLHG reduces to the GIVDHFUUBLHG operator.

Theorem 16. All the proposed generalized operators GIVDHFUUBLWA, GIVDHFUUBLWG, GIVDHFUUBLWA, GIVDHFUUBLWG, GIVDHFUUBLHA, GIVDHFUUBLHG, I-GIVDHFUUBLHA, and I-GIVDHFUUBLHG hold the following properties: (1) Commutativity; (2) Idempotency; (3) Boundedness.

Based on above theorems, following properties can also be derived.

Theorem 17. For a collection of IVDHF_UUBLNs $sd_j = (\bar{s}_{\theta_j}, \bar{h}_j, \bar{g}_j)$, $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$ is the weight vector of sd_j with $\omega_j \in [0, 1]$ and $\sum_{j=1}^n \omega_j = 1$, $\lambda > 0$; then we have

- (1) $IVDHFUUBLWG_{\omega}(sd_1, sd_2, \dots, sd_n) \leq IVDHFUUBLWA_{\omega}(sd_1, sd_2, \dots, sd_n)$;
- (2) $IVDHFUUBLWG_{\omega}(sd_1, sd_2, \dots, sd_n) \leq GIVDHFUUBLWA_{\omega, \lambda}(sd_1, sd_2, \dots, sd_n)$;
- (3) $GIVDHFUUBLWG_{\omega, \lambda}(sd_1, sd_2, \dots, sd_n) \leq IVDHFUUBLWA_{\omega}(sd_1, sd_2, \dots, sd_n)$.

Proof. Omitted for concision. $\square$

Theorem 18. For a collection of IVDHF_UUBLNs $sd_j = (\bar{s}_{\theta_j}, \bar{h}_j, \bar{g}_j)$, $w = (w_1, w_2, \dots, w_n)^T$ is the weighting vector of sd_j with $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$, $\lambda > 0$. Then,

- (1) $IVDHFUUBLWG_w(sd_1, sd_2, \dots, sd_n) \leq IVDHFUUBLWA_w(sd_1, sd_2, \dots, sd_n)$;
- (2) $IVDHFUUBLWG_w(sd_1, sd_2, \dots, sd_n) \leq GIVDHFUUBLWA_{w, \lambda}(sd_1, sd_2, \dots, sd_n)$;
- (3) $GIVDHFUUBLWG_{w, \lambda}(sd_1, sd_2, \dots, sd_n) \leq IVDHFUUBLWA_w(sd_1, sd_2, \dots, sd_n)$.

Proof. Omitted for concision. $\square$

5. An Integrated MADM Approach for Tackling Complex Green Contractor Selection Problems

As described in Section 2, we take the green contractor selection as a special type of complicate MADM problems that synthesizes three characteristics of decision hesitancy [21, 22], attributes interdependency [84], and group attitudinal characters [61]. Therefore, in this section, we construct an integrated MADM approach to tackle the complex green contractor selection problems. Suppose $X = \{x_1, x_2, \dots, x_m\}$ is the set of alternative green contractors and $A = \{A_1, A_2, \dots, A_n\}$ is the set of evaluative attributes. $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$ is weighting vector for the attributes, $\omega_i \geq 0$, $\sum_{i=1}^n \omega_i = 1$. Let $\tilde{R} = (\tilde{r}_{ij})_{n \times m}$ denote the decision matrix in which $\tilde{r}_{ij} = ([s_{\alpha_{ij}}, s_{\beta_{ij}}], \tilde{h}_{ij}, \tilde{g}_{ij})$ is an IVDHF_UUBLN given by decision-makers for alternative contractor x_j with respect to attribute A_i . According to the mechanism of pair-wise comparisons among attributes in the DEMATEL method [63, 64], the interdependency among attributes can be obtained as a matrix $\tilde{Z} = (z_{i,k})_{n \times n}$, where $z_{i,k}$ indicates the degree to which A_i affects A_k . Subsequently, based on the IVDHFUUBLN and its operations, we now present detailed steps of our MADM approach as shown in following Algorithm I.

Algorithm I. Hesitant fuzzy linguistic MADM with attributes interdependency and decision-makers' group attitudinal characters.

Step 1. Determine argument-dependent weighting vector ω^{AD} according to attribute values by programming model developed in the following Section 5.1.

Step 2. Obtain the attribute-interdependences based weighting vector ω^{AI} by use of DEMATEL method described in the following Section 5.2.

Step 3. Calculate synthesized attribute weighting vector according to

$$\omega = \alpha \omega^{AI} + \beta \omega^{AD}, \quad (19)$$

where α and β are parameters to reflect decision characteristics of decision organizations, $0 \leq \alpha, \beta \leq 1$, $\alpha + \beta = 1$.

Step 4. Check requirements for order inducing. If no additional order inducing required, then go to Step 5; otherwise go to Step 6.

Step 5. Utilize generalized aggregation operators to get the overall IVDHF_UUBLNs $\tilde{r}_j (j = 1, \dots, m)$ for each alternative x_j . Here we take GIVDHFUUBLHA operator for example because it can include other traditional operators as its special cases. Therefore, we have

$$\begin{aligned} \text{GIVDHFUUBLHA}(\tilde{r}_{1j}, \tilde{r}_{2j}, \dots, \tilde{r}_{nj}) &= \left(\bigoplus_{i=1}^n (w_i (\tilde{r}_{\sigma_{ij}})^\lambda) \right)^{1/\lambda} \\ &= \bigcup_{(\tilde{s}_{\sigma_{ij}}, \tilde{h}_{\sigma_{ij}}, \tilde{g}_{\sigma_{ij}}) \in \tilde{r}_{\sigma_{ij}}} \left(\left[\bar{s}_{\left(\sum_{i=1}^n w_i (\Delta_{t_0}^{-1} (TF_{t_0}^{t_{j1}} (\psi(\tilde{s}_{\alpha_{\sigma_{ij}}}))^\lambda) \right)^{1/\lambda}}, \bar{s}_{\left(\sum_{i=1}^n w_i (\Delta_{t_0}^{-1} (TF_{t_0}^{t_{j2}} (\psi(\tilde{s}_{\beta_{\sigma_{ij}}}))^\lambda) \right)^{1/\lambda}} \right], \right. \\ &\quad \left. \bigcup_{[\mu_{\sigma_{ij}}^L, \mu_{\sigma_{ij}}^U] \in \tilde{h}_{\sigma_{ij}}, [\nu_{\sigma_{ij}}^L, \nu_{\sigma_{ij}}^U] \in \tilde{g}_{\sigma_{ij}}} \left\{ \left[\left(1 - \prod_{i=1}^n \left(1 - (\mu_{\sigma_{ij}}^L)^\lambda \right)^{w_i} \right)^{1/\lambda}, \left(1 - \prod_{i=1}^n \left(1 - (\mu_{\sigma_{ij}}^U)^\lambda \right)^{w_i} \right)^{1/\lambda} \right] \right\}, \right. \\ &\quad \left. \left\{ \left[1 - \left(1 - \prod_{i=1}^n \left(1 - (1 - \nu_{\sigma_{ij}}^L)^\lambda \right)^{w_i} \right)^{1/\lambda}, 1 - \left(1 - \prod_{i=1}^n \left(1 - (1 - \nu_{\sigma_{ij}}^U)^\lambda \right)^{w_i} \right)^{1/\lambda} \right] \right\} \right\} \right), \end{aligned} \quad (20)$$

where $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$ is the weighting vector of $\tilde{r}_{ij}$, $w = (w_1, w_2, \dots, w_n)^T$ is the aggregation-associated weight vector, $\tilde{r}_{\sigma_{ij}}$ is the i th largest of $\tilde{r}_{ij}$, and

$$\begin{aligned} \tilde{r}_{ij} = n \omega_i \tilde{r}_{ij} &= \bigcup_{(\tilde{s}_{ij}, \tilde{h}_{ij}, \tilde{g}_{ij}) \in \tilde{r}_{ij}} \left(\left[s_{n \omega_i (\Delta_{t_0}^{-1} (TF_{t_0}^{t_{j1}} (\psi(s_{\alpha_{ij}})))^\lambda)}, s_{n \omega_i (\Delta_{t_0}^{-1} (TF_{t_0}^{t_{j2}} (\psi(s_{\beta_{ij}})))^\lambda)} \right], \right. \\ &\quad \left. \bigcup_{[\mu_{ij}^L, \mu_{ij}^U] \in \tilde{h}_{ij}, [\nu_{ij}^L, \nu_{ij}^U] \in \tilde{g}_{ij}} \left\{ \left[1 - (1 - \mu_{ij}^L)^{n \omega_i}, 1 - (1 - \mu_{ij}^U)^{n \omega_i} \right], \left[(1 - \nu_{ij}^L)^{n \omega_i}, (1 - \nu_{ij}^U)^{n \omega_i} \right] \right\} \right). \end{aligned} \quad (21)$$

Then go to Step 8.

Step 6. By use of the TOPSIS-based method developed in the following Section 5.3, we determine order-inducing vectors ε to reflect decision-makers' group attitudinal characters.

Step 7. Utilizing induced generalized aggregation operators to get the overall IVDHF_UUBLNs $\tilde{r}_j (j = 1, 2, \dots, m)$ for each alternative x_j , we have

$$\begin{aligned}
 I\text{-GIVDHFULHA}(\tilde{r}_{1j}, \tilde{r}_{2j}, \dots, \tilde{r}_{nm}) &= \left(\bigoplus_{i=1}^n \left(w_i (\tilde{r}_{\pi_{ij}})^\lambda \right) \right)^{1/\lambda} \\
 &= \bigcup_{(\tilde{s}_{\pi_{ij}}, \tilde{h}_{\pi_{ij}}, \tilde{g}_{\pi_{ij}}) \in \tilde{r}_{\pi_{ij}}} \left(\left[\bar{s}_{\left(\sum_{j=1}^n w_i (\Delta_{t_0}^{-1} (TF_{t_0}^{t_{j1}} (\psi(\tilde{s}_{\alpha_{\pi_{ij}})})))^\lambda \right)^{1/\lambda}}, \bar{s}_{\left(\sum_{j=1}^n w_i (\Delta_{t_0}^{-1} (TF_{t_0}^{t_{j2}} (\psi(\tilde{s}_{\beta_{\pi_{ij}})})))^\lambda \right)^{1/\lambda}} \right], \right. \\
 &\quad \left. \bigcup_{(\tilde{\mu}_{\pi_{ij}}^L, \tilde{\mu}_{\pi_{ij}}^U) \in \tilde{h}_{\pi_{ij}}, (\tilde{\nu}_{\pi_{ij}}^L, \tilde{\nu}_{\pi_{ij}}^U) \in \tilde{g}_{\pi_{ij}}} \left\{ \left[\left(1 - \prod_{i=1}^n \left(1 - (\tilde{\mu}_{\pi_{ij}}^L)^\lambda \right)^{w_i} \right)^{1/\lambda}, \left(1 - \prod_{i=1}^n \left(1 - (\tilde{\mu}_{\pi_{ij}}^U)^\lambda \right)^{w_i} \right)^{1/\lambda} \right] \right\}, \right. \\
 &\quad \left. \left\{ \left[1 - \left(1 - \prod_{i=1}^n \left(1 - (1 - \tilde{\nu}_{\pi_{ij}}^L)^\lambda \right)^{w_i} \right)^{1/\lambda}, 1 - \left(1 - \prod_{i=1}^n \left(1 - (1 - \tilde{\nu}_{\pi_{ij}}^U)^\lambda \right)^{w_i} \right)^{1/\lambda} \right] \right\} \right\} \right),
 \end{aligned} \tag{22}$$

where $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$ is the weighting vector of $\tilde{r}_{ij}$, $w = (w_1, w_2, \dots, w_n)^T$ is the aggregation-associated

weighting vector, $\tilde{r}_{\pi_{ij}}$ is the i th largest of $\tilde{r}_{ij}$ reordered by the order-inducing vectors ε , and

$$\begin{aligned}
 \tilde{r}_{ij} = n\omega_i \tilde{r}_{ij} &= \bigcup_{(\tilde{s}_{ij}, \tilde{h}_{ij}, \tilde{g}_{ij}) \in \tilde{r}_{ij}} \left(\left[s_{n\omega_i (\Delta_{t_0}^{-1} (TF_{t_0}^{t_{j1}} (\psi(s_{\alpha_{ij}})))) n\omega_i \alpha_{ij}}, s_{n\omega_i (\Delta_{t_0}^{-1} (TF_{t_0}^{t_{j1}} (\psi(s_{\beta_{ij}}))))} \right], \right. \\
 &\quad \left. \bigcup_{(\tilde{\mu}_{ij}^L, \tilde{\mu}_{ij}^U) \in \tilde{h}_{ij}, (\tilde{\nu}_{ij}^L, \tilde{\nu}_{ij}^U) \in \tilde{g}_{ij}} \left\{ \left[1 - (1 - \mu_{ij}^L)^{n\omega_i}, 1 - (1 - \mu_{ij}^U)^{n\omega_i} \right], \left[(1 - \nu_{ij}^L)^{n\omega_i}, (1 - \nu_{ij}^U)^{n\omega_i} \right] \right\} \right).
 \end{aligned} \tag{23}$$

Step 8. Calculate scores $S(\tilde{r}_j)$ and accuracy degrees $P(\tilde{r}_j)$ for $\tilde{r}_j, (j = 1, 2, \dots, m)$;

Step 9. According to Definition 5, output ranking order of alternative contractors.

In Algorithm I, to objectively derive unknown weighting vector for evaluative attributes, a synthesized attribute weighting vector is devised by fusing two parts of concern: (i) argument-dependent weighting vector and (ii) attribute-interdependences based weighting vector. The former is to reflect effects of attribute values on attribute weights, while the latter is to exploit effects of interdependences among attributes on their weights. For clarity, processing flowchart of Algorithm I is depicted in Figure 3.

5.1. Determining Argument-Dependent Attribute Weighting Vector ω^{AD} . In order to derive attribute weighting vector appropriately from assessments, maximizing deviation method [91] is adopted here for its distinguishing ability

and objectivity [92]. According to Wang [91], if performance values of each alternative have little differences under an attribute, it implicates such an attribute plays a less important role; otherwise, it lives a more important role in decision-making. Thus, if one attribute has similar values across alternatives, it should be assigned a smaller weight; contrariwise, it should be a bigger weight.

In light of the idea in maximizing deviation method, we develop a programming model to determine argument-dependent weighting vector ω^{AD} . For attribute A_i , the standard deviation of alternative x_j to all the other alternatives is denoted as

$$F_{ij}(\omega^{AD}) = \sum_{l=1}^m d(\tilde{r}_{ij}, \tilde{r}_{il}) \omega_i^{AD}, \tag{24}$$

$$i = 1, 2, \dots, n; j = 1, 2, \dots, m.$$

Let $F_i(\omega^{AD})$ represent deviation value of all alternatives to other alternatives according to attribute A_i and be formulated as follows:

FIGURE 3: Processing flowchart of Algorithm I.

$$F_i(\omega^{AD}) = \sum_{j=1}^m F_{ij}(\omega^{AD}) = \sum_{j=1}^m \sum_{l=1}^m d(\tilde{r}_{ij}, \tilde{r}_{il}) \omega_i^{AD}, \quad (25)$$

$i = 1, 2, \dots, n; j = 1, 2, \dots, m.$

Based on the analysis above, we can get following programming model (M-1) for obtaining optimal attribute weighting vector ω^{AD} :

$$(M-1) \begin{cases} \max & F(\omega^{AD}) = \sum_{i=1}^n F_i(\omega^{AD}) = \sum_{i=1}^n \sum_{j=1}^m \sum_{l=1}^m d(\tilde{r}_{ij}, \tilde{r}_{il}) \omega_i^{AD} \\ \text{s.t.} & \sum_{i=1}^n (\omega_i^{AD})^2 = 1, \quad \omega_i^{AD} \geq 0, \quad i = 1, 2, \dots, n, \end{cases} \quad (26)$$

where $d(\tilde{r}_{ij}, \tilde{r}_{il})$ can be calculated by Definition 6.

To solve model (M-1), we can construct Lagrange function:

$$L(\omega_i^{AD}, \zeta) = \sum_{i=1}^n \sum_{j=1}^m \sum_{l=1}^m d(\tilde{r}_{ij}, \tilde{r}_{il}) \omega_i^{AD} + \frac{\zeta}{2} \left(\sum_{i=1}^n (\omega_i^{AD})^2 - 1 \right), \quad (27)$$

where ζ is the Lagrange multiplier.

Differentiate with respect to ω_i^{AD} ($i = 1, 2, \dots, m$) and ζ , and set these partial derivatives equal to zero; the following set of equations can be obtained:

$$\frac{\partial L}{\partial \omega_i^{AD}} = \sum_{j=1}^m \sum_{l=1}^m d(\tilde{r}_{ij}, \tilde{r}_{il}) + \zeta \omega_i^{AD} = 0 \quad (28)$$

$$\frac{\partial L}{\partial \zeta} = \sum_{i=1}^n (\omega_i^{AD})^2 - 1 = 0.$$

By normalizing the solutions of above equations, we can get a simple and exact formula for determining the attribute weights as follows:

$$\omega_i^{AD} = \frac{\sum_{j=1}^m \sum_{l=1}^m d(\tilde{r}_{ij}, \tilde{r}_{il})}{\sum_{i=1}^n \sum_{j=1}^m \sum_{l=1}^m d(\tilde{r}_{ij}, \tilde{r}_{il})}. \quad (29)$$

5.2. Deriving Attributes Interdependency-Based Attribute Weighting Vector ω^{AI} . Some efforts [53, 60, 84, 93–95]

have been made to address interdependencies between attributes in MADM. However, they unanimously cannot reveal the interdependencies in a more complete way. While DEMATAEL technique [63, 96] gathers collective knowledge to capture influences between attributes more precisely and completely, so that weighting vector for attributes can be rationally determined according to strength measure of those influences [64, 97]. Therefore, in tackling the complex MADM with interdependent attributes under IVDHF_UUBL environments, we present a DEMATEL-based method as the following Algorithm II to derive attribute weighting vector ω^{AI} from the viewpoint of attributes interdependency.

Algorithm II. DEMATEL-based method for ensuring weighting vector ω^{AI} .

Step 1. Construct initial direct-influence matrix $Z = (z_{ik})_{n \times n}$.

For attributes $A = \{A_1, A_2, \dots, A_n\}$, decision-makers are asked to give direct effect that attribute A_i has on attribute A_k , using a five-point scale with scores represented by natural language: (1) 0 — ‘absolutely no influence’; (2) 1 — ‘low influence’; (3) 2 — ‘medium influence’; (4) 3 — ‘high influence’; (5) 4 — ‘very high influence.’ Then, the initial direct-influence matrix $Z = (z_{ik})_{n \times n}$ can be established, with each element being the mean of same factors in different direct matrices.

Step 2. Calculate normalized direct-influence matrix $X = (x_{ik})_{n \times n}$. Using matrix Z , the normalized direct-influence matrix $X = (x_{ik})_{n \times n}$ is calculated according to

$$x_{ik} = \frac{z_{ik}}{s}, \quad (30)$$

where $s = \max\{\max_{1 \leq i \leq n} \sum_{k=1}^n z_{ik}, \max_{1 \leq k \leq n} \sum_{i=1}^n z_{ik}\}$. All elements in matrix X are complying with $0 \leq x_{ik} \leq 1$, $0 \leq \sum_{k=1}^n x_{ik} \leq 1$, and $0 \leq \sum_{i=1}^n x_{ik} \leq 1$, and at least one row or column of the summation equals 1.

Step 3. Derive total-influence matrix $T = (t_{ik})_{n \times n}$. Based on matrix X , the total-influence matrix $T = (t_{ik})_{n \times n}$ can be derived by summing the direct effects and all of the indirect effects,

$$T = X + X^2 + X^3 + \dots + X^h = X(I - X)^{-1}, \quad (31)$$

where I represents identity matrix. When $h \rightarrow \infty$, $X^h = (0)_{n \times n}$.

Step 4. Compute influencing and influenced degrees of each attribute. The sum of rows and the sum of columns within the total-influence matrix T are, respectively, expressed as the vectors r and c :

$$\begin{aligned} r &= (r_i)_{n \times 1} = \left(\sum_{k=1}^n t_{ik} \right)_{n \times 1}, \\ c &= (c_k)_{n \times 1} = \left(\sum_{i=1}^n t_{ik} \right)_{1 \times n}^T, \end{aligned} \quad (32)$$

where r_i denotes the sum of the i th row in matrix T and shows the sum of direct and indirect effects that attribute A_i has on other attributes. Similarly, c_k shows the sum of direct and indirect effects that attribute A_k has received.

Step 5. Estimate weights of attributes based on influence degrees, according to

$$\omega_i^{I*} = \left[(r_i + c_i)^2 + (r_i - c_i)^2 \right]^{1/2}. \quad (33)$$

Then, the weighting vector ω^{AI} can be obtained by normalizing (33):

$$\omega_i^{AI} = \frac{\omega_i^{I*}}{\sum_{i=1}^n \omega_i^{I*}}. \quad (34)$$

5.3. Obtaining Order Inducing Variables ε by TOPSIS-Based Method. For ill-defined MADM problems, induced aggregation operators [89, 90, 98] provide an effective channel for experts to express complex attitudinal characters. The key step in induced aggregation operators is to obtain order-inducing vectors ε which, however, are presumptively assigned in most papers [62]. Therefore, in this section, aiming at deducing the order-inducing vectors ε rationally, we here devise a TOPSIS-based method in Algorithm III. Obviously, the Algorithm III is of generality for MADM with different forms of linguistic expression.

Algorithm III. TOPSIS-based method for obtaining order inducing vectors ε .

Step 1. Let the decision maker define IVDHF_UUBL ideal solution(s) $\tilde{r}_i^+$ and IVDHF_UUBL negative ideal solution(s) $\tilde{r}_i^-$ corresponding to each attribute, in which

$$\begin{aligned} \tilde{r}_i^+ &= (\tilde{r}_{i1}^+, \tilde{r}_{i2}^+, \dots, \tilde{r}_{ip}^+), \\ \tilde{r}_i^- &= (\tilde{r}_{i1}^-, \tilde{r}_{i2}^-, \dots, \tilde{r}_{iq}^-), \end{aligned} \quad (35)$$

where p and q denotes the number of $\tilde{r}_i^+$ and $\tilde{r}_i^-$ respectively.

Step 2. Calculate distances from each element in decision matrix to ideal solution(s) and negative solution(s) respectively:

$$\begin{aligned} d_{ij}^+ &= \max_{l=1,2,\dots,p} d(\tilde{r}_{ij}, \tilde{r}_{il}^+), \\ d_{ij}^- &= \min_{l=1,2,\dots,q} d(\tilde{r}_{ij}, \tilde{r}_{il}^-), \end{aligned} \quad (36)$$

where $d(\tilde{r}_{ij}, \tilde{r}_{il}^+)$ and $d(\tilde{r}_{ij}, \tilde{r}_{il}^-)$ are calculated by the distance measure in Definition 6. If $p > 1$, we choose the one with maximum distance; if $q > 1$, we choose the one with minimum distance.

Step 3. Calculate coefficients according to

$$c_{ij} = \frac{d_{ij}^-}{d_{ij}^+ + d_{ij}^-}, \quad i = 1, 2, \dots, n; \quad j = 1, 2, \dots, m. \quad (37)$$

TABLE 2: Decision matrix $\tilde{R}$ in the form of IVDHF_UUBLS.

	x_1	x_2	x_3
A_1	([AH, VH], {[0.2, 0.3]}, [0.2, 0.4], [0.3, 0.4])	([H, T], {[0.4, 0.5]}, [0.5, 0.6], {[0.2, 0.3], [0.2, 0.4]})	([AL, AH], {[0.1, 0.2]}, [0.1, 0.3], {[0.6, 0.7]})
A_2	([M, H], {[0.5, 0.6]}, [0.2, 0.3])	([AH, T], {[0.6, 0.7]}, [0.1, 0.2])	([M, VH], {[0.2, 0.3]}, [0.5, 0.6], [0.6, 0.7])
A_3	([VL, AL], {[0.3, 0.4]}, [0.4, 0.5], [0.5, 0.6])	([M, VH], {[0.6, 0.7], [0.7, 0.8]}, [0.1, 0.2])	([VL, L], {[0.4, 0.5]}, [0.2, 0.3])
A_4	([M, AH], {[0.2, 0.4]}, [0.5, 0.6])	([L, AL], {[0.3, 0.5]}, [0.2, 0.3])	([AL, M], {[0.6, 0.7]}, [0.1, 0.2], [0.2, 0.3])
A_5	([AL, M], {[0.4, 0.5]}, [0.1, 0.2], [0.4, 0.5])	([AH, H], {[0.6, 0.7]}, [0.1, 0.2])	([H, VH], {[0.4, 0.5]}, [0.6, 0.7], {[0.1, 0.3]})
A_6	([L, M], {[0.1, 0.2], [0.3, 0.5]}, {[0.3, 0.5]})	([VL, L], {[0.2, 0.4], [0.5, 0.6]}, [0.2, 0.3])	([AH, H], {[0.3, 0.4]}, [0.4, 0.5])
A_7	([VL, L], {[0.4, 0.5], [0.5, 0.6]}, {[0.2, 0.3], [0.2, 0.4]})	([M, AH], {[0.5, 0.6], [0.7, 0.8]}, [0.1, 0.2])	([AL, M], {[0.4, 0.5], [0.5, 0.6]}, {[0.3, 0.4]})
A_8	([AL, AH], {[0.1, 0.3]}, [0.4, 0.6])	([AH, H], {[0.5, 0.7]}, [0.1, 0.2], [0.2, 0.3])	([AH, H], {[0.4, 0.6]}, [0.3, 0.4])

TABLE 3: Direct influence matrix Z.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A_1	0	3	4	1	3	1	2	4
A_2	1	0	2	4	4	2	3	1
A_3	4	2	0	1	3	2	4	1
A_4	2	3	1	0	3	4	1	2
A_5	4	2	1	3	0	1	4	3
A_6	2	4	3	4	4	0	4	2
A_7	4	1	2	3	3	1	0	4
A_8	1	2	4	3	3	2	4	0

Step 4. Derive order inducing variable ε_{ij} by descending order of c_{ij} . The greater the value c_{ij} , the bigger the ε_{ij} .

6. Illustrative Example and Experiments

6.1. Illustrative Case Study. Suppose a mega infrastructure project is selecting green contractor for one of its subprojects. A panel of decision-makers including managers, professors and competitive intelligence experts has been organized to comprehensively evaluate three alternative contractors (i.e., x_1 , x_2 and x_3) under the eight attributes (i.e., A_1 – A_8) listed in Section 2.

To elicit true decision preferences, we apply the IVDHF_UUBLS to assess the three alternatives (x_1 – x_3). Firstly, decision-makers are asked to vote on x_j under each attribute A_i using different unbalanced linguistic term sets S_1 , S_2 and S_3 , where $S_1 = \{N, L, AL, M, AH, H, QH, VH, AT, T\}$, $S_2 = \{N, AN, VL, QL, L, AL, M, AH, VH, T\}$, $S_3 = \{N, VL, L, AM, M, QM, AH, H, T\}$. In Figure 4, we show the adopted linguistic hierarchies and relationship between S_1 , S_2 and S_3 . Attributes A_1 , A_2 , A_5 and A_8 are evaluated by use of S_1 , attributes A_3 , A_4 and A_7 are evaluated by S_2 , and attribute A_6 is evaluated by S_3 . The highest-voted uncertain unbalanced linguistic term $[s_m, s_n]$ are identified. Secondly, the panel of

decision-makers is asked to further express their opinions on membership degrees $\tilde{h}(x)$ and nonmembership degrees $\tilde{g}(x)$ to $[s_m, s_n]$. Then we can derive compound assessments (i.e., $\langle x, \tilde{s}_{\theta(x)}, \tilde{h}(x), \tilde{g}(x) \rangle$) in the form of IVDHF_UUBLS and obtain the decision matrix $\tilde{R}$ in Table 2. Additionally, in order to examine the interdependency among attributes, decision-makers are also required to assess the influential relations among the eight attributes, using DEMATEL-based Algorithm II. The direct influence matrix is collected and shown in Table 3.

Next, we apply the proposed Algorithm I to solve this green contractor selection problem. To derive the synthesized attribute weighting vector in Algorithm I, we assign $\alpha = \beta = 0.5$. For scenarios with no group attitudinal characters, operator GIVDHFUUBLHA in Definition 12 is chosen. In contrast, for scenarios with group attitudinal characters, operator I-GIVDHFUUBLHA in Definition 13 will be chosen. Further, the panel of decision-makers is asked to determine their positive and negative ideal alternatives that are collected in Table 4, where corresponding order-inducing vectors that are derived from Algorithm III are also listed (see the rightmost column). Thereafter, operator I-GIVDHFUUBLHA in Definition 13 is utilized for aggregation. For GIVDHFUUBLHA and I-GIVDHFUUBLHA, we

TABLE 4: Ideal alternatives (r^+ and r^-) and derived order-inducing vectors ε .

	r^+	r^-	x_1	x_2	x_3
A_1	([VH, T], {1}, {0})	([N, L], {1}, {0})	5	6	6
A_2	([M, AH], {[0.7, 0.8]}, {[0.1, 0.2]})	([N, L], {1}, {0})	1	1	4
A_3	(T, {1}, {0})	(L, {1}, {0})	8	7	8
A_4	([AL, AH], {0.9}, {0.1})	(T, {1}, {0})	2	2	1
A_5	([H, T], {[0.9, 1]}, {0})	(N, {1}, {0})	7	5	5
A_6	(M, {1}, {0})	(N, {1}, {0})	6	3	3
A_7	(M, {1}, {0})	([N, L], {1}, {0})	3	8	7
A_8	([M, AH], {1}, {0})	(N, {1}, {0})	4	4	2

FIGURE 4: Unbalanced linguistic term sets (S_1 , S_2 , and S_3) and their mapping in linguistic hierarchies.

assume $\lambda=2$, and $w = (0, 0, 0.15, 0.25, 0.25, 0.25, 0.1, 0)^T$. Note that w is a position weighting vector, which is derived by the fuzzy semantic quantitative operator [99]. After completing all steps in Algorithm I (see Appendix C), we obtain the ranking results and present them in Table 5. For the scores derived from Step 5, we find the ranking order is $x_2 > x_3 > x_1$, indicating that x_2 is the best solution. Step 7 gives the ranking order of $x_2 > x_1 > x_3$, indicating x_2 is still the most appropriate one, while x_1 is better than x_3 under the influence of ε .

6.2. Experiments on Ranking Results along with Various Parameter Configurations. In order to inspect the impacts of various parameter configurations on ranking results, in this section, more numerical examples are carried out. All eight operators that defined in Section 4.1 are applied to the above illustrative case, where the parameter λ is configured as integers ranging from 1 to 20 and parameter α is configured to a value set of $\{0, 0.3, 0.5, 0.8, 0.9, 1\}$.

Firstly, the four basic aggregation operators of GIVDHFUUBLWA, GIVDHFUUBLWG, GIVDHFUUBLOWA and

TABLE 5: Ranking results of operators GIVDHFUUBLHA and I-GIVDHFUUBLHA.

Aggregation operator	Ranking order
GIVDHFUUBLHA	$x_2 > x_3 > x_1$
I-GIVDHFUUBLHA	$x_2 > x_1 > x_3$

GIVDHFUUBLOWG are applied to the former case. The same configuration $\alpha = \beta = 0.5$ is chosen while λ is tested as integers ranging from 1 to 20. The ranking results derived from different parameter combinations have been collected in Table 6. As can be seen, four operators unanimously identify the contractor x_2 is the best one no matter how λ changes. Regarding priority relation between x_1 and x_3 , GIVDHFUUBLWA and GIVDHFUUBLOWA generate the same result of $x_3 > x_1$; while results from GIVDHFUUBLWG and GIVDHFUUBLOWG got a change to $x_1 > x_3$ at a certain value of parameter λ .

Actually, GIVDHFUUBLWA and GIVDHFUUBLOWA are generalized version of weighted arithmetic aggregation operators that produce more favorable results by emphasizing

TABLE 6: Ranking orders obtained by GIVDHFUUBLWA, GIVDHFUUBLWA, GIVDHFUUBLWG, and GIVDHFUUBLWG along with λ .

Operators	λ (Integer)	Ranking order
GIVDHFUUBLWA	[1, 20]	$x_2 > x_3 > x_1$
GIVDHFUUBLWA	[1, 20]	$x_2 > x_3 > x_1$
GIVDHFUUBLWG	[1, 2]	$x_2 > x_3 > x_1$
	[3, 20]	$x_2 > x_1 > x_3$
GIVDHFUUBLWG	[1, 8]	$x_2 > x_3 > x_1$
	[9, 20]	$x_2 > x_1 > x_3$

TABLE 7: Ranking results obtained by GIVDHFUUBLHA and I-GIVDHFUUBLHA along with α , β , and λ .

α, β	λ (Integer)	GIVDHFUUBLHA	I-GIVDHFUUBLHA
$\alpha=0, \beta=1$	[1, 20]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
$\alpha=0.3, \beta=0.7$	[1, 20]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
$\alpha=0.5, \beta=0.5$	[1, 20]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
$\alpha=0.8, \beta=0.2$	[1, 20]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
$\alpha=0.9, \beta=0.1$	[1, 20]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
$\alpha=1, \beta=0$	[1, 20]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$

TABLE 8: Ranking results obtained by GIVDHFUUBLHG and I-GIVDHFUUBLHG along with α , β , and λ .

α, β	λ (Integer)	GIVDHFUUBLHG	I-GIVDHFUUBLHG
$\alpha = 0, \beta = 1$	[1, 7]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
	[8, 20]	$x_2 > x_1 > x_3$	$x_2 > x_1 > x_3$
$\alpha = 0.3, \beta = 0.7$	[1, 7]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
	[8, 20]	$x_2 > x_1 > x_3$	$x_2 > x_1 > x_3$
$\alpha = 0.5, \beta = 0.5$	[1, 8]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
	[9, 20]	$x_2 > x_1 > x_3$	$x_2 > x_1 > x_3$
$\alpha = 0.8, \beta = 0.2$	[1, 17]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
	[18, 20]	$x_2 > x_1 > x_3$	$x_2 > x_1 > x_3$
$\alpha = 0.9, \beta = 0.1$	[1, 20]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$
$\alpha = 1, \beta = 0$	[1, 20]	$x_2 > x_3 > x_1$	$x_2 > x_1 > x_3$

membership degrees to a uncertain linguistic term thus can be considered as optimistic operators, while GIVDHFUUBLWG and GIVDHFUUBLWG are generalized geometric aggregation operators that produce more favorable results by emphasizing nonmembership degrees thus can be considered as pessimistic operators [100, 101]. Therefore, the ranking results in Table 6 could be perceived as: for optimism-based decision-making, alternative x_3 always stands out better than x_1 when λ gradually amplifies degree of optimism; but for pessimism-based decision-making, x_1 turns out better than x_3 when λ gradually amplifies degree of pessimism. λ can be considered as the parameter for amplifying degree of optimism or pessimism [101].

Next, to inspect the impacts of various combinations of ω^{AI} and ω^{AD} on ranking results, another four aggregation operators of GIVDHFUUBLHA, GIVDHFUUBLHG, I-GIVDHFUUBLHA and I-GIVDHFUUBLHG also have been applied to the above illustrative case with varying α , β and λ .

All results have been collected in Tables 7 and 8 for comparison. As can be seen from Table 7, ranking results generated by operator GIVDHFUUBLHA keep the same as $x_2 > x_3 > x_1$ for all test combinations of parameters. However, as shown in Table 8, although GIVDHFUUBLHG is also capable of identifying x_2 as the best contractor, the priority relations between x_1 and x_3 hold similar changing patterns in ranking results in Table 6 that were output by GIVDHFUUBLWG and GIVDHFUUBLWG. Regarding decision situations where objective attribute weighting vector ω^{AD} is only considered ($\alpha = 0$) or its dominant importance (such as $\alpha = 0.3$) is accepted, $x_1 > x_3$ is a clear observation when parameter λ is set to an integer in interval [8, 20]. Contrariwise, under decision scenarios where subjective attribute weighting vector ω^{AI} is only needed ($\alpha = 1$) or its dominant importance (such as $\alpha = 0.9$) is acknowledged, $x_3 > x_1$ holds all the way λ varies.

In order to more clearly show the score trajectories of alternative contractors along variations of parameter λ , we

FIGURE 5: Score trajectories obtained by aggregation operators HA and InducedHA with different configuration of α : (a) $\alpha = 0$, (b) $\alpha = 0.3$, (c) $\alpha = 0.5$, (d) $\alpha = 0.7$, (e) $\alpha = 0.9$, and (f) $\alpha = 1$.

further configure parameter λ to the value set of $[0:0.1:100]$ and conduct computational experiments to collect score values and ranking results (as shown in Figures 5 and 6) by four aggregation operators of GIVDHFUUBLHA, GIVDHFUUBLHG, I-GIVDHFUUBLHA and I-GIVDHFUUBLHG. For more clarity in Figures 5 and 6, please note that we use HA, HG, Induced-HA and Induced HG to respectively denote GIVDHFUUBLHA, GIVDHFUUBLHG, I-GIVDHFUUBLHA and I-GIVDHFUUBLHG. In Figure 5, it can be observed that when dominant importance of ω^{AD}

is emphasized ($\alpha = 0, \alpha = 0.3, \alpha = 0.5$), GIVDHFUUBLHA is capable of differentiating the three alternative contractors as same ranking order of $x_2 > x_3 > x_1$ for all λ ; but with increases in α , the margins between scores of x_1 and x_3 narrows and the rank order changes to $x_1 > x_3$ when α gets 0.9 and 1. Interestingly in Figure 6, although GIVDHFUUBLHG is able to significantly differentiate alternative contractors x_1 and x_3 when dominant importance of ω^{AD} is emphasized ($\alpha = 0, \alpha = 0.3, \alpha = 0.5$), rank order of x_1 and x_3 obviously changes once from $x_3 > x_1$ to $x_1 > x_3$ when λ is bigger

FIGURE 6: Score trajectories obtained by aggregation operators HG and InducedHG with different configuration of α : (a) $\alpha = 0$, (b) $\alpha = 0.3$, (c) $\alpha = 0.5$, (d) $\alpha = 0.7$, (e) $\alpha = 0.9$, and (f) $\alpha = 1$.

than 8. When α increases to 1, GIVDHFUUBLHG maintains the rank order of $x_3 > x_1$, but their score trajectories walk very close. Comparatively, I-GIVDHFUUBLHA and I-GIVDHFUUBLHG generate consistent ranking results of $x_2 > x_1 > x_3$ no matter λ varies in all the above experiments.

In sum, when parameters are configured with typical values (i.e., $\alpha = 0.5$ and $\lambda = 1$) and no additional attitudinal information is taken into consideration, the proposed aggregation operators unanimously derive the same rank order $x_2 > x_3 > x_1$ of for the three alternative contractors. However,

with the amplification effect of parameter λ , analysis results from linear combination of ω^{AI} and ω^{AD} reveal alternative x_2 which consistently is the best choice but rank order of x_1 and x_3 changes because their score trajectories get close and crossed, which probably indicates that only decision-making information derived from the decision matrix is inadequate to significantly differentiate alternatives x_1 and x_3 . While by integrating additional decision information about attitudinal characters of group experts, I-GIVDHFUUBLHA and I-GIVDHFUUBLHG manage to generate the identical

TABLE 9: Order-inducing vectors obtained by our TOPSIS-based method for problem in [38].

	G_1	G_2	G_3	G_4
A_1	0.2522	0.1629	0.2282	0.2714
A_2	0.1	0.5243	0.1364	0.4689
A_3	0.4081	0.1756	0.5244	0.3779
A_4	0.4507	0.1409	0.1064	0.1322
A_5	0.0697	0.2203	0.3753	0.1161

TABLE 10: Order-inducing vectors obtained by our TOPSIS-based method for problem in [39].

	G_1	G_2	G_3	G_4
A_1	0.4548	0.4969	0.4923	0.4732
A_2	0.5092	0.47	0.4768	0.4645
A_3	0.7192	0.4888	0.4953	0.4915
A_4	0.6722	0.6163	0.5706	0.4929
A_5	0.6104	0.4942	0.6463	0.4946

TABLE 11: Ranking results obtained by applying different order-inducing vectors to [38, 39].

Problems	Approaches	Ranking results
Problem in [38]	IHFLOWA [38] + order-inducing vectors in [38]	$A_3 > A_1 > A_2 > A_5 > A_4$
	IHFLOWA [38] + order-inducing vectors in Table 9	$A_3 > A_1 > A_2 > A_4 > A_5$
Problem in [39]	I-IVDHFLOWA [39] + order-inducing vectors in [39]	$A_4 > A_3 > A_5 > A_2 > A_1$
	I-IVDHFLOWA [39] + order-inducing vectors in Table 10	$A_4 > A_3 > A_5 > A_1 > A_2$

permutation of $x_2 > x_1 > x_3$, which verifies that our proposed TOPSIS-based order-inducing approach is practical and useful in helping work out decision results more reasonably and robustly.

6.3. Application Studies of Proposed TOPSIS-Based Order-Inducing Method. When confronting complex decision-making situations that need additional attitudinal characters of decision-makers, Yager and Filev [88] and Yager [102] introduced and encouraged to employ order-inducing vector to represent those attitudinal characters. Since then, the idea of order-inducing vector has been extended to various decision-making environments [98, 103], such as those based on intuitionistic fuzzy information [104, 105], linguistic information [106], hesitant fuzzy linguistic information [38], and interval-valued dual hesitant fuzzy uncertain linguistic information [39]. Generally, in existing literature, order-inducing vectors rely on experts to directly give [38, 39, 104–106].

In order to examine the adaptability of our TOPSIS-based order-inducing method to linguistic decision-making environments, we respectively apply the method to resolve the same problems in references [38, 39]. Due to fact that there is no descriptions about how the order-inducing vectors were derived in both references [38, 39], we here apply extremums into our TOPSIS-based method to obtain order-inducing vectors, that is, $(s_7, \{1\}, \{0\})$ and $(s_1, \{0\}, \{1\})$ for [38], $([s_6, s_6], \{1\}, \{0\})$, and $([s_0, s_0], \{0\}, \{1\})$ for [39]. Then we obtain our order-inducing vectors listed in Table 9 for the problem adopted in [38], and our order-inducing vectors listed in Table 10 for [39].

Now, we apply the order-inducing vectors as shown in Tables 9 and 10 to resolve the problems in [38] and [39], respectively. Regarding the problem in [38], the score values of all alternatives are calculated as $S(A_1)=0.2602$, $S(A_2)=0.2417$, $S(A_3)=0.3577$, $S(A_4)=0.221$, and $S(A_5)=0.185$; so the corresponding ranking result is $A_3 > A_1 > A_2 > A_4 > A_5$. As for the problem in [39], the score values of all alternatives are computed as $S(A_1)=3.9954$, $S(A_2)=3.783$, $S(A_3)=7.0827$, $S(A_4)=7.1792$, and $S(A_5)=5.813$; we thus obtain the ranking result $A_4 > A_3 > A_5 > A_1 > A_2$. For more clarity, brief descriptions of comparative approaches and obtained ranking results also have been put together in Table 11.

According to Table 11, the approaches that employ our order-inducing vectors derive the same ranking order of the better three alternatives for both comparative problems from [38, 39]. As seen, our proposed TOPSIS-based order-inducing method exhibits effective and more understandable. Furthermore, when decision-makers are incapable of directly put forward all desired order-inducing vectors due to complexity in ill-structured problems, our method provides a feasible directions to obtain order-inducing vectors by figuring out ideal solutions. Comparatively, our proposed TOPSIS-based order-inducing method behaves effective and more operational in practical use.

6.4. Comparison with Decision-Making Approach Based on Degraded form of IVDHFULS. Note that our approach is intrinsically adaptive to decision situations based on degraded forms of IVDHF_UUBLS, such as the dual hesitant

fuzzy linguistic sets introduced by Yang and Ju [54]. To further inspect feasibility of our approach, we here conduct comparative study on the same case adopted by Yang and Ju [54]. We firstly convert their original decision matrix into the form of IVDHF_UUBLS: crisp membership and non-membership degrees are equivalently changed to intervals with same upper and lower limits (e.g., 0.2 turns out to be $[0.2, 0.2]$), and linguistic variables are rewritten as uncertain linguistic variables (e.g., s_2 turns out to be $[s_2, s_2]$).

Since the case only got three attributes, among which interdependency could be not significant under general assumption, weighting vector ω^{AI} is not calculated. And for straight comparison, order inducing vector is not included either. Then, the argument-dependent attribute weighting vector can be obtained from Eq.(29) as $\omega^{AD} = (0.3192, 0.3132, 0.3676)^T$. By use of Algorithm I with operator IVDHFUUBLWA (i.e., GIVDHFUUBLWA in case of $\lambda = 1$, see Appendix B), we have the scores of alternatives: $s(A_1) = 0.3412, s(A_2) = 0.1354, s(A_3) = 0.3932, s(A_4) = 0.7352$. Therefore, the ordering of alternatives is $A_4 > A_3 > A_1 > A_2$, which is mainly in alignment with the ordering of $A_4 > A_1 > A_3 > A_2$ in Yang and Ju [54]. It is worth noticing that ω^{AD} used in our approach is derived objectively from assessments, while attribute weights $\omega^* = (0.35, 0.25, 0.40)^T$ used by Yang and Ju [54] were assigned empirically. Differences between ω^{AD} and ω^* lead to different ordering of A_1 and A_3 . Comparatively speaking, our approach holds more adaptability and objectivity.

In general, our proposed MADM approach in this paper exhibits an effective way to tackle complex green contractor selection problems, in which subjective attributes weighting vector (such as ω^{AI}) and objective attributes weighting vector (such as ω^{AD}) exist. To comprehensively utilize these two fundamental facets of attributes weighting information, our case study and computational experiments suggest that linear combination method (i.e., $\omega = \alpha\omega^{AI} + \beta\omega^{AD}$) is effective to reflect effects of ω^{AI} and ω^{AD} by configuring parameter α or β . When there is no specific expert opinions to specify or hard to obtain, we suggest that parameter α chooses the value set of $\{0, 0.2, 0.5, 0.8, 1\}$. Furthermore, generalized aggregation operators are suggested to inspect score trajectories of alternative contractors along increasing of the operators' amplification parameter λ . If some alternative contractors' score values get very close or crossed so that they cannot be differentiated from each other significantly, we suggest to ask the panel of experts to derive opinions of ideal solutions and utilize our TOPSIS-based order-inducing method to include those expert opinions as attitudinal decision information, thereby obtaining more rational and robust decision results.

7. Conclusions

Aiming at tackling complex decision-making problems of green contractor selection that often hold simultaneously the characteristics of decision hesitancy, attributes interdependency, and group complex attitudinal characters, we have developed an effective IVDHF_UUBLS-based approach.

We utilize IVDHF_UUBLS to elicit complicate decision-makers' assessments more objectively and comprehensively, we employ DEMATEL for addressing attribute interdependency more precisely, and we determine group attitudinal characters as order-inducing vectors based on ideal attitudes of experts rather than by empirical assignment. The main advantages of our approach are (i). IVDHF_UUBLS offers an adequate way to depict decision hesitancy; (ii). the designed distance measure for IVDHF_UUBLS avoids information distortion of traditional ones, which artificially add mismatching membership or nonmembership degrees; (iii). the developed generalized operators include traditional ones as special cases so as to provide flexibility in MADM based on IVDHF_UUBLS; (iv). the devised synthesized attribute weighting scheme provides an adaptive way to consider two necessary aspects: attributes interdependency-based weights and argument-dependent weights; (v). the TOPSIS-based method can deduce reasonable order-inducing vectors rather than empirical ones and holds generality in other linguistic decision environments. Results of case studies and experiments have verified the validity of the proposed approach.

When multiple decision organizations are involved, group decision-making based on IVDHF_UUBLS is an important research direction. Besides inducing preferences, for decision-making problems of high uncertainty, interactive mechanisms should also be studied to extract preferences. In addition, empirical studies of the proposed approach can be carried out to various areas, such as investment evaluation project management and vehicle selection in fleet operations.

Appendix

A. Basic Notions for IVDHFS and Unbalanced Linguistic Term Set

Definition A.1 (see [47]). Letting X be a fixed set, then an IVDHFS on X is defined as

$$\tilde{D} = \{ \langle x, \tilde{h}(x), \tilde{g}(x) \rangle \mid x \in X \}, \quad (A.1)$$

where $\tilde{h}(x) = \bigcup_{[\mu^L, \mu^U] \in \tilde{h}(x)} \{\tilde{\mu}\} = \bigcup_{[\mu^L, \mu^U] \in \tilde{h}(x)} \{[\mu^L, \mu^U]\}$ and $\tilde{g}(x) = \bigcup_{[\nu^L, \nu^U] \in \tilde{g}(x)} \{\tilde{\nu}\} = \bigcup_{[\nu^L, \nu^U] \in \tilde{g}(x)} \{[\nu^L, \nu^U]\}$ are two sets of interval values in $[0, 1]$, denoting possible membership and non-membership degrees of element $x \in X$ to the set $\tilde{D}$, respectively; with conditions: $\tilde{\mu}, \tilde{\nu} \in [0, 1]$ and $0 \leq (\mu^U)^+ + (\nu^U)^+ \leq 1$; and for all $x \in X$, $(\mu^U)^+ \in \tilde{h}^+(x) = \bigcup_{[\mu^L, \mu^U] \in \tilde{h}(x)} \max\{\mu^U\}$ and $(\nu^U)^+ \in \tilde{g}^+(x) = \bigcup_{[\nu^L, \nu^U] \in \tilde{g}(x)} \max\{\nu^U\}$.

For convenience, normally $\tilde{d} = \{\tilde{h}, \tilde{g}\}$ is called an interval-valued dual hesitant fuzzy element (IVDHFE), and $\tilde{D}$ is the set of all IVDHFEs.

Definition A.2 (see [107]). Suppose $S = \{s_j \mid j = 0, 1, \dots, g-1\}$ is a finite and totally ordered discrete linguistic term set, where s_j represent possible values for a linguistic variable and g is an odd cardinality. S is uniformly and symmetrically distributed if the following two conditions are satisfied: (1)

there exists a unique constant $\lambda > 0$ such that $NS(s_i) - NS(s_j) = l(i - j)$ for all $i, j = 0, 1, \dots, g - 1$; (2) Let $S_R = \{s \mid s \in S, s > S_C\}$ and $S_L = \{s \mid s \in S, s < S_C\}$. Let $\mathbb{C}(S_R)$ and $\mathbb{C}(S_L)$ be the cardinality of S_R and S_L , then $\mathbb{C}(S_R) = \mathbb{C}(S_L)$. If S is uniformly and symmetrically distributed, then S is called a balanced linguistic term set. Otherwise, S is called an unbalanced linguistic term set.

The following 2-tuple fuzzy linguistic representation model extends traditional linguistic term set to a continuous case so as to facilitate computing with linguistic variables.

Definition A.3 (see [59]). Let $S = \{s_0, s_1, \dots, s_{g-1}\}$ be a linguistic term set and $\beta \in [0, g]$. Then a 2-tuple fuzzy linguistic variable expresses the equivalent information to β is defined as

$$\Delta : [0, g] \longrightarrow S \times [-0.5, 0.5], \quad (\text{A.2})$$

$$\Delta(\beta) = (s_i, \alpha),$$

$$\text{with } \begin{cases} s_i, & i = \text{round}(\beta) \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5], \end{cases} \quad (\text{A.3})$$

$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta, \quad (\text{A.4})$$

where $\text{round}(\cdot)$ is the usual rounding operation and α is called symbolic translation.

To obtain 2-tuple fuzzy linguistic representations of unbalanced linguistic terms, the concept of linguistic hierarchies, i.e., $LH = \bigcup_t l(t, n(t))$, is used. $l(t, n(t))$ is a linguistic hierarchy with t indicating the level of hierarchy and $n(t)$ denotes the granularity of the linguistic term set of t . Herrera, et al. [59] defined the following transformation functions between labels from different levels in multigranular linguistic information contexts without loss of information.

Definition A.4 (see [59]). In linguistic hierarchies $LH = \bigcup_t l(t, n(t))$ whose linguistic term sets are represented by $S^{n(t)} = \{s_0^{n(t)}, \dots, s_{n(t)-1}^{n(t)}\}$, the transformation function from a linguistic label in level t to a label in consecutive level t' is defined as $TF_{t'}^t : l(t, n(t)) \longrightarrow l(t', n(t'))$ such that

$$\begin{aligned} & TF_{t'}^t(s_i^{n(t)}, \alpha^{n(t)}) \\ &= \Delta_{t'} \left(\frac{\Delta_t^{-1}(s_i^{n(t)}, \alpha^{n(t)}) (n(t') - 1)}{n(t) - 1} \right). \end{aligned} \quad (\text{A.5})$$

By use of the above transformation function, any 2-tuple linguistic representation can be transformed into a term in LH . Detailed transformation procedures are listed as follows.

(1) Representation in linguistic hierarchy. To transform the unbalanced terms of S into the corresponding terms in the LH , transformation function ψ is employed to associate each unbalanced linguistic 2-tuple (s_i, α) with its linguistic 2-tuple in $LH(\bar{S})$, i.e.,

$$\psi : \bar{S} \longrightarrow LH(\bar{S}), \quad (\text{A.6})$$

so that $\psi(s_i, \alpha) = (s_{I(i)}^{G(i)}, \lambda)$, for $\forall (s_i, \alpha) \in \bar{S}$.

(2) Computational phase. Firstly, transform $(s_{I(i)}^{G(i)}, \lambda)$ into linguistic 2-tuples, denoted as $(s_{I'(i)}^{n(t')}, \lambda')$ in $\bar{S}^{n(t')}$, where

$$\begin{aligned} (s_{I'(i)}^{n(t')}, \lambda') &= TF(s_{I(i)}^{G(i)}, \lambda) \\ &= \Delta \left(\frac{\Delta^{-1}(s_{I(i)}^{G(i)}, \lambda) \cdot (n(t') - 1)}{G(i) - 1} \right). \end{aligned} \quad (\text{A.7})$$

Then, a computational model is used over $\bar{S}^{n(t')}$ with a result denoted as $(s_r^{n(t')}, \lambda_r) \in \bar{S}^{n(t')}$.

(3) Retranslation process. The result $(s_r^{n(t')}, \lambda_r) \in \bar{S}^{n(t')}$ is transformed into the unbalanced term in $\bar{S}$, by using the transformation function ψ^{-1} , i.e.,

$$\psi^{-1} : LH(\bar{S}) \longrightarrow \bar{S}, \quad (\text{A.8})$$

so that $\psi^{-1}(s_r^{n(t')}, \lambda_r) = (s_{\text{result}}, \lambda_{\text{result}}) \in \bar{S}$.

B. Details of Theorem 14

Proof. Given a collection of IVDHF_UUBLNs $sd_j = (\tilde{s}_{g_j}, \tilde{h}_j, \tilde{g}_j)$, $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$ is the weighting vector for sd_j and $w = (w_1, w_2, \dots, w_n)^T$ is the aggregation-associated weighting vector, $\lambda > 0$, then,

(1) If $\lambda \neq 1$

(1) If $w = (1/n, 1/n, \dots, 1/n)^T$, then GIVDHFUUBLHA and GIVDHFUUBLHG operators reduce to the GIVDHFUUBLWA and GIVDHFUUBLWG operators, respectively;

(2) If $w = (1/n, 1/n, \dots, 1/n)^T$, then GIVDHFUUBLHA and GIVDHFUUBLHG operators reduce to the GIVDHFUUBLWA and GIVDHFUUBLWG operators, respectively.

(2) If $\lambda = 1$

(1) If $w = (1/n, 1/n, \dots, 1/n)^T$, then GIVDHFUUBLHA and GIVDHFUUBLHG operators reduce to the IVDHF_UUBL weighted average (IVDHFUUBLWA) and IVDHF_UUBL weighted geometric (IVDHFUUBLWG) operators, respectively, where

$$\begin{aligned}
IVDHFUUBLWA_{\omega}(sd_1, sd_2, \dots, sd_n) &= \bigoplus_{j=1}^n \omega_j sd_j \\
&= \bigcup_{(\tilde{s}_{\theta_j}, \tilde{h}_j, \tilde{g}_j) \in sd_j} \left(\left[S_{\sum_{j=1}^n \omega_j (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j1}}(\psi(s_{\alpha_j}))))}, S_{\sum_{j=1}^n \omega_j (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j2}}(\psi(s_{\beta_j}))))} \right] \right. \\
&\quad \left. \bigcup_{[\mu_j^L, \mu_j^U] \in \tilde{h}_j, [\nu_j^L, \nu_j^U] \in \tilde{g}_j} \left\{ \left\{ \left[1 - \prod_{j=1}^n (1 - \mu_j^L)^{\omega_j}, 1 - \prod_{j=1}^n (1 - \mu_j^U)^{\omega_j} \right] \right\}, \left\{ \left[\prod_{j=1}^n (\nu_j^L)^{\omega_j}, \prod_{j=1}^n (\nu_j^U)^{\omega_j} \right] \right\} \right\} \right);
\end{aligned} \tag{B.1}$$

$$\begin{aligned}
IVDHFUUBLWG_{\omega}(sd_1, sd_2, \dots, sd_n) &= \bigotimes_{j=1}^n sd_j^{\omega_j} \\
&= \bigcup_{(\tilde{s}_{\theta_j}, \tilde{h}_j, \tilde{g}_j) \in sd_j} \left(\left[S_{\prod_{j=1}^n (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j1}}(\psi(s_{\alpha_j}))))^{\omega_j}}, S_{\prod_{j=1}^n (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j2}}(\psi(s_{\beta_j}))))^{\omega_j}} \right] \right. \\
&\quad \left. \bigcup_{[\mu_j^L, \mu_j^U] \in \tilde{h}_j, [\nu_j^L, \nu_j^U] \in \tilde{g}_j} \left\{ \left\{ \left[\prod_{j=1}^n (\mu_j^L)^{\omega_j}, \prod_{j=1}^n (\mu_j^U)^{\omega_j} \right] \right\}, \left\{ \left[1 - \prod_{j=1}^n (1 - \nu_j^L)^{\omega_j}, 1 - \prod_{j=1}^n (1 - \nu_j^U)^{\omega_j} \right] \right\} \right\} \right);
\end{aligned} \tag{B.2}$$

(2) If $\omega = (1/n, 1/n, \dots, 1/n)^T$, then GIVDHFUUBLHA and GIVDHFUUBLHG operators reduce to the IVDHF_UUUBL

ordered weighted average (IVDHFUUBLWA) and IVDHF_UUUBL ordered weighted geometric (IVDHFUUBLWG) operators, respectively, where

$$\begin{aligned}
IVDHFUUBLWA_w(sd_1, sd_2, \dots, sd_n) &= \bigoplus_{j=1}^n w_j sd_{\sigma(j)} \\
&= \bigcup_{(\tilde{s}_{\theta_{\sigma(j)}}, \tilde{h}_{\sigma(j)}, \tilde{g}_{\sigma(j)}) \in sd_{\sigma(j)}} \left(\left[S_{\sum_{j=1}^n w_j \Delta_{t_0}^{-1}(TF_{t_0}^{t_{j1}}(\psi(s_{\alpha_{\sigma(j)}})))}, S_{\sum_{j=1}^n w_j \Delta_{t_0}^{-1}(TF_{t_0}^{t_{j2}}(\psi(s_{\beta_{\sigma(j)}})))} \right] \right. \\
&\quad \left. \bigcup_{[\mu_{\sigma(j)}^L, \mu_{\sigma(j)}^U] \in \tilde{h}_{\sigma(j)}, [\nu_{\sigma(j)}^L, \nu_{\sigma(j)}^U] \in \tilde{g}_{\sigma(j)}} \left\{ \left\{ \left[1 - \prod_{j=1}^n (1 - \mu_{\sigma(j)}^L)^{w_j}, 1 - \prod_{j=1}^n (1 - \mu_{\sigma(j)}^U)^{w_j} \right] \right\}, \left\{ \left[\prod_{j=1}^n (\nu_{\sigma(j)}^L)^{w_j}, \prod_{j=1}^n (\nu_{\sigma(j)}^U)^{w_j} \right] \right\} \right\} \right);
\end{aligned} \tag{B.3}$$

$$\begin{aligned}
IVDHFUUBLWG_w(sd_1, sd_2, \dots, sd_n) &= \bigotimes_{j=1}^n sd_{\sigma(j)}^{w_j} \\
&= \bigcup_{(\tilde{s}_{\theta_{\sigma(j)}}, \tilde{h}_{\sigma(j)}, \tilde{g}_{\sigma(j)}) \in sd_{\sigma(j)}} \left(\left[S_{\prod_{j=1}^n (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j1}}(\psi(s_{\alpha_{\sigma(j)}}))))^{w_j}}, S_{\prod_{j=1}^n (\Delta_{t_0}^{-1}(TF_{t_0}^{t_{j2}}(\psi(s_{\beta_{\sigma(j)}}))))^{w_j}} \right] \right. \\
&\quad \left. \bigcup_{[\mu_{\sigma(j)}^L, \mu_{\sigma(j)}^U] \in \tilde{h}_{\sigma(j)}, [\nu_{\sigma(j)}^L, \nu_{\sigma(j)}^U] \in \tilde{g}_{\sigma(j)}} \left\{ \left\{ \left[\prod_{j=1}^n (\mu_{\sigma(j)}^L)^{w_j}, \prod_{j=1}^n (\mu_{\sigma(j)}^U)^{w_j} \right] \right\}, \left\{ \left[1 - \prod_{j=1}^n (1 - \nu_{\sigma(j)}^L)^{w_j}, 1 - \prod_{j=1}^n (1 - \nu_{\sigma(j)}^U)^{w_j} \right] \right\} \right\} \right).
\end{aligned} \tag{B.4}$$

Overall, we can conclude the relationship between all these proposed aggregation operators as shown in Theorem 14. $\square$

C. Computation Steps of Algorithm I

Step 1. Determine argument-dependent weighting vector ω^{AD} .

$$\omega^{AD} = (0.1383, 0.171, 0.1597, 0.1059, 0.102, 0.0902, 0.1202, 0.1127)^T. \quad (C.1)$$

Step 2. Determine attributes interdependency-based weighting vector ω^{AI} .

After processing Step 4 in Algorithm II, the influencing and influenced degrees of each attribute can be obtained as

$$\omega^{AI} = (0.1248, 0.1149, 0.1158, 0.121, 0.1379, 0.1255, 0.135, 0.1251)^T. \quad (C.2)$$

Step 3. Obtain synthesized attributes weighting vector.

To comprehensively consider attribute weighting information, synthesized weighting vector is computed by (19) in which α and β are set as 0.5,

$$\omega = (0.1316, 0.143, 0.1377, 0.1135, 0.12, 0.1078, 0.1276, 0.1188)^T. \quad (C.3)$$

Step 4. Check order inducing requirements.

After consulting the expert team, if there is no group attitudinal characters (i.e., order inducing vectors), then go to Step 5; otherwise go to Step 6.

Step 5. Derive overall IVDHF_UUBLNs $\tilde{r}_j$ of each alternative x_j ($j = 1, 2, 3$).

Here, we choose GIVDHFUUBLHA operator in Definition 12 and assign $\lambda = 2$. The associated position weighting vector is assigned as $\omega = (0, 0, 0.15, 0.25, 0.25, 0.25, 0.1, 0)^T$, which is acquired by commonly used fuzzy semantic quantitative operator with parameters (a, b) set as (0.3, 0.8) [99]. Then we get the values of $\tilde{r}_1$, $\tilde{r}_2$, and $\tilde{r}_3$. Taking $\tilde{r}_3$, for example, we have

$$\begin{aligned} \tilde{r}_3 = & ([s_{3.5754}, s_{4.8345}], \{ \{ [0.36594, 0.48336], \\ & [0.36594, 0.48336], [0.39856, 0.51409], \\ & [0.39856, 0.51409], [0.36594, 0.48336], \\ & [0.36594, 0.48336], [0.39856, 0.51409], \\ & [0.39856, 0.51409] \}, \{ [0.29622, 0.39832], \\ & [0.30123, 0.4036], [0.29622, 0.39832], \\ & [0.30123, 0.4036] \} \}). \end{aligned} \quad (C.4)$$

Utilize the programming model (M-1) in Section 4.1; by calculating (29), we get

shown in Table 2. Then according to (33) and (34), weighting vector based on attributes interdependency is determined as

Later on, $\tilde{r}_1$, $\tilde{r}_2$, and $\tilde{r}_3$ will be fed into Step 8 to calculate scores and accuracy degrees of each contractor.

Step 6. Derive order-inducing vectors ε .

According to the TOPSIS-based method described in Algorithm III, decision-makers are required to put forward both IVDHF_UUBL ideal alternatives and IVDHF_UUBL negative ideal alternatives. As listed in Table 3, the ideal solution and negative ideal solution are collected, based on which the order-inducing vectors ε are derived by sorting the coefficients generated out of (37).

Step 7. Utilize induced generalized aggregation operators to get the overall IVDHFUBBLNs $\tilde{r}_j$ ($j = 1, 2, \dots, m$) of each alternative x_j .

After order-inducing vector ε is obtained, I-GIVDHFUUBLHA operator defined in Definition 13 is chosen for information aggregation, λ and position weights are set same as in Step 5, and then we can obtain $\tilde{r}_1$, $\tilde{r}_2$ and $\tilde{r}_3$. Taking $\tilde{r}_3$ as an example, we have

$$\begin{aligned} \tilde{r}_3 = & ([s_{4.0762}, s_{5.877}], \{ \{ [0.31061, 0.43001], \\ & [0.31061, 0.43548], [0.34999, 0.46638], \\ & [0.34999, 0.47123], [0.31061, 0.43001], \\ & [0.31061, 0.43548], [0.34999, 0.46638], \\ & [0.34999, 0.47123] \}, \{ [0.39075, 0.49203], \\ & [0.39075, 0.49203], [0.40918, 0.51064], \\ & [0.40918, 0.51064] \} \}); \end{aligned} \quad (C.5)$$

Step 8. Calculate scores and accuracy degrees of each solution.

Now we can utilize the score function and accuracy function defined in Definition 4 to calculate scores $S(\tilde{r}_j)$ and accuracy degrees $P(\tilde{r}_j)$ of each $\tilde{r}_j$. For each $\tilde{r}_j$ generated from Step 5, we have $S_{GIVDHFUUBLHA}(\tilde{r}_1) = -0.146$, $S_{GIVDHFUUBLHA}(\tilde{r}_2) = 2.157$, and $S_{GIVDHFUUBLHA}(\tilde{r}_3) = 0.381$. And for each $\tilde{r}_j$ generated from Step 7, we have $S_{I-GIVDHFUUBLHA}(\tilde{r}_1) = 0.136$, $S_{I-GIVDHFUUBLHA}(\tilde{r}_2) = 1.962$, and $S_{I-GIVDHFUUBLHA}(\tilde{r}_3) = -0.299$.

Step 9. Generate final ranking results.

According to the scores obtained from Step 5 and the comparative rules defined in Definition 5, the ranking order is $x_2 > x_3 > x_1$, indicating that x_2 is the most appropriate solution. Regarding the scores obtained from Step 7, the ranking order is $x_2 > x_1 > x_3$, indicating that x_2 is still the most appropriate solution and solution x_1 is better than solution x_3 . Ranking results are then collected in Table 4 for clarity.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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