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ORIGINAL ARTICLE

A novel integrated approach based on best–worst and VIKOR methods for green supplier selection under multi-granularity extended probabilistic linguistic environment

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Abstract

With consideration for the extensive resources consumption and environmental degradation being on the rise today, implementing green development strategy to pursue both socioeconomic growth and the coordinated of environment sustainability, has become an increasingly important issue in modern enterprise supply chain operations management. Hence, the appropriate green supplier selection (GSS), viewed as a core issue in green supply chain management (GSCM), requires continuous research in this field to obtain a complete perception on GSS practices. It can be regarded as a multi-attribute group decision-making (MAGDM) problem that involves many conflict and unmeasurable evaluation criteria. In view of the superiority of multi-granularity extended probabilistic linguistic term sets (MGEPLTSs) in modeling such issues on potential ambiguity, complexity and uncertainty in actual GSS practices, we propose a novel integrated MAGDM methodology for GSS problems, by integrating the BWM (best–worst method) with the VIKOR (VIšekriterijumsko KOmpromisno Rangiranje) technique under the MGEPLTSs environment. First, by introducing the multi-granularity and probabilistic linguistic term sets, the MGEPLTSs are proposed to represent and quantify the decision information of GSCM practitioners. Then, the BWM is introduced to the MGEPLTSs environment to compute the weights of decision-making panels and evaluation attributes in GSS problems, by building the fuzzy mathematical programming model, respectively. Finally, we extend a multi-granularity extended probabilistic linguistic VIKOR method to calculate the compromise measure of alternatives considering the group utility maximization and the individual regret minimization, thereby achieving the full ranking of alternatives. A GSS case is conducted to illustrate the feasibility of the proposed approach, and the sensitivity analysis and comparative analysis with other similar approaches are presented to demonstrate its effectiveness and advantages.

Keywords Multi-granularity extended probabilistic linguistic term sets · Best–worst method · VIKOR method · Multi-attribute group decision making · Green supplier selection

Introduction

The essence of green development commonly means a sustainable development pattern, namely using concrete recommendations and measurement tools to meet human needs to achieve socioeconomic growth, while preserving the environment and conserves energy to provide the continuous ecosystems services [39]. The green development strategy proposes a flexible policy framework that can be tailored to different country circumstances and stages of development. In view of the resource depletion and environmental degradation being on the rise today, carrying out the green development strategy to trade-off the economic benefit and the environment friendliness becomes an increasingly important issue in modern enterprise supply chain operations management. Consequently, the conception of green supply chain management (GSCM) proposed in 1996 has gradually become a hot topic and popular research direction [5, 16]. GSCM has emerged as a new modern management mode that comprehensively considers environmental impact

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and resource efficiency [20]. In GSCM operations management, the green supplier focuses strictly on the whole process from product design to final recycling, such as green product design, green procurement, green supply, green production, green marketing, green packaging, and resource recycling [42, 50].

As an essential part of the green supply chain, supplier selection plays an important role in the survival and sustainable development of enterprises. Therefore, a growing number of leading companies begin to transform their production and operations mode and are now proactively implementing “green” initiative [37, 40, 50]. For instance, the IEKA company, as a largest furniture manufacturer, stressed the “greenness” of train operations on its new train transportation network. What is more, the HP and IBM are regarding “green” as an important worth in enterprise value system for maintaining good public images. Specifically, they adopted new energy saving technology in green product design and also attempted to enhance supply chain management capability to deal with environmental concerns such as CO2 emission and solid waste produced. Among multiple green-related practices, enterprises have been guided to the green innovation, because it is an indispensable component in achieving the dual goals of environmental degradation and economic development [42]. In GSCM operations, the green supplier selection (GSS) is the core component and can directly determine the environment protection performance of manufacturers.

There are large number of studies on the supplier selection concerned with the environmental issues through the emerging conception GSCM. In GSCM practices, the supply chain managers are always required to take all suppliers with many conflicting evaluation criteria, including resource consumption, green production, green marketing, green packaging, product life cycle cost, and so on, and then consider the trade-off to select the optimal supplier. Hence, GSS is commonly regarded as a multi-attribute group decision-making (MAGDM) problem [12, 18, 28, 32]. The MAGDM methods help the individual or group of decision-makers to take appropriate and transparent decisions in complex situations. It helps to determine the ranking of alternatives and choosing the superior one using an appropriate method based on some criteria. It has been applied in a wide range of applications such as social sciences, engineering, health care, economics and management [1, 46, 51]. For GSS problems in practice, the most of detailed evaluation information is unknown and full of diversity and uncertainty. Accordingly, the classical type-1 fuzzy sets are commonly insufficient to simulate the real situations due to the increasing diversity, uncertainty and complexity of the GSS problems [32]. In such cases, it is more appropriate and direct for supply chain managers to use linguistic information to represent decision information due to the complex environment.

Many scholars have proved the usefulness of linguistic information and proposed different types of linguistic expression [10, 22, 33, 49, 58, 61], such as linguistic term sets (LTSs), probabilistic linguistic term sets (PLTSs), double hierarchy hesitant fuzzy linguistic term set and probabilistic double hierarchy linguistic term set. Because the GSS is usually made by many supply chain managers together and they cannot use a single linguistic term to describe decision information. In such situation, the PLTSs are suitable to reflect group opinions. The PLTSs not only allow supply chain managers to describe preferences, but also reflect the important degrees of linguistic terms [30]. In addition, in the actual evaluation process, because some supply chain managers give hesitant fuzzy linguistic elements, the sum of probability distribution in probability linguistic elements may be greater than 1. Therefore, we extend the PLTSs and rename it extended probability linguistic term sets (EPLTSs), and use the EPLTSs to describe the decision information of supply chain managers. However, there is a limitation that supply chain managers cannot use their linguistic labels to express preferences. Due to the different knowledge and experience, supply chain managers usually express their preference by multi-granularity linguistic labels in group decision-making [23]. Hence, we attempt to combine the multi-granularity and EPLTSs and propose a new multi-granularity extended probability linguistic term sets (MGEPLTSs) to characterize the decision information in GSS problems.

Under the multi-granularity extended probabilistic linguistic environment, the supply chain managers need to select some different MAGDM methods, such as VIKOR (VIšekriterijumsko KOmpromisno Rangiranje), TODIM (TOmada de Decisão Interativa Multicritério), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), prospect theory, and so on, to achieve the full ranking of all green suppliers in GSCM operations. Yazdani et al. [56] developed an integrated quality function deployment based MAGDM model for selecting a suitable green supplier. Govindan et al. [15] proposed a novel PROMETHEE-based hybrid method to construct a group compromise ranking for GSS problems in food supply chain. Verdecho et al. [48] introduced a multi-attribute methodology to choose supplier based on sustainability strategy and applied the proposed method to assess the sustainability of agri-food supplier selection. Asadabadi et al. [2] developed a novel stratified BWM-TOPSIS criteria decision framework to evaluate supplier performance of organizations considering the environmental sustainability. Wu and Liao [54] introduced a multi-attribute decision-making method with geometric linguistic scale for green supplier selection in agricultural product.

With consideration for the complexity and diversity of objective features and the disturbance from internal or external ambiguity and uncertainty, it is commonly impossible for supply chain managers to obtain information by specific exact values, and for such cases via fuzzy information to express preferences is obviously more realistic. Consequently, many studies applied the fuzzy set-based MAGDM approach to address GSS problems in GSCM practices. For example, Rostamzadeh et al. [36] introduced an extended fuzzy VIKOR approach to examine GSS problems, and they presented the preferences of supply chain managers using triangular fuzzy numbers. Qin et al. [32] proposed a novel extended TODIM approach for GSS under the interval type-2 fuzzy environment. By introducing the fuzzy ANP, the multi-objective mathematical programming and the DEMATEL, Bakeshlou et al. [4] constructed a novel integrated MAGDM method for selecting an appropriate green supplier. Wu et al. [53] proposed an integrated approach based on the interval type-2 fuzzy best–worst and extended VIKOR methods and applied to green supplier selection. Compared with the existing type-1 fuzzy sets, the interval type-2 fuzzy model is capable of handling the parameter uncertainties of membership functions because of its low computational complexity and high efficiency [41, 59, 62]. Hence, many excellent studies have been presented for the stabilization of interval type-2 fuzzy systems, such as Tao et al. [43] and Zhang et al. [59, 62]. Liou et al. [25] proposed a combined fuzzy BWM (best—worst method) and fuzzy TOPSIS methods to assess and select green suppliers. Masoomi et al. [28] integrated two MAGDM methods, namely the COPRAS and WASPAS, with the fuzzy BWM for selecting a strategic green supplier.

Since the convenience and flexibility of fuzzy sets in representing uncertainty, many studies related to GSS problems transitioned from exact numbers to a fuzzy environment. According to the preceding reviews of relevant studies, nowadays the VIKOR method has gradually attracted more and more attentions from scholars and has already been applied to deal with GSS problems in various situations because of its superiorities in solving GSS problems [3, 9, 36, 53]. The VIKOR method has some characteristics and capabilities compared to other MAGDM approaches. For example, compared with the TOPSIS and TODIM method, the VIKOR not only can consider the group utility maximization and the individual regret minimization, but also can fully reflect the subjective preferences of decision-makers [6, 8, 29, 53]. For discrete decision problems under the conflicting and non-commensurable (for different units) criteria, it can provide the optimal solution which is the closest to the actual situation. What is more, it focuses on the selection and priority of a series of alternatives and can determine the just results for the issues under conflicting criteria, thereby helping the decision-makers to obtain a consensus decision. On the other hand, compared with the prospect theory, the VIKOR method does not need a standard expectation level. To further handle the imprecision and uncertainty inherent in the measurement of the GSS practitioners' processes, it is necessary to use the MGEPLTSs to address the vagueness in GSCM practices. However, although the VIKOR method has already been developed from various perspectives, there are almost no relevant studies on extending the VIKOR method to MGEPLTSs environment. Because of the advantages of the VIKOR method and MGEPLTSs discussed above, in this paper we attempt to introduce the VIKOR method to MGEPLTSs environment to obtain the optimal green supplier in GSCM practices.

In addition, since supply chain managers distinguish the optimal supplier from diverse indexes, and the index weights are important in the MAGDM, so how to determine the index weights has also gained more and more attentions. At present, the methods to deal with weights include AHP (analytic hierarchy process) method, ANP (analytic network process) method, BWM, etc. [27, 45, 58, 61]. Since the BWM simplifies the tedious process of AHP and the errors caused by experts' confusion due to excessive data are reduced, it has already been developed from various perspectives using fuzzy theories and applied to many MAGDM problems [21, 31, 44]. The BWM is a classic method to determine the subjective weight of indexes proposed by Dutch scholar Rezaei in 2015 [35]. Yazdi et al. [57] used an extension of best–worst method based on democratic-autocratic decision-making style to make the reliable risk analysis. Lahri et al. [19] used a combined BWM and fuzzy TOPSIS approaches to assess green image weights of suppliers. The BWM is also useful in other fields, for instance evaluating the performance for smart bike-sharing programs [47], measuring the environmental performance [26], assessing the scientific output quality [38], etc. Therefore, we attempt to combine the BWM with MGEPLTSs to address index weights in MAGDM process for solving GSS problems.

In outline, the main objective of this study is to propose a novel integrated MAGDM approach under the multi-granularity extended probabilistic linguistic environment, by integrating the MGEPLTSs with the BWM and VIKOR method. The proposed approach can solve GSS problems considering the imprecision and uncertainty inherent in the measurement of the GSS practitioners' processes. Compared to previous studies, the main contributions of our study can be concluded as follows:

- In the inspiration of PLTSs, we extend a new MGEPLTSs to quantify the decision information of GSS problems given by the GSCM practitioners to address the issues on potential ambiguity and uncertainty in actual GSCM practices, which can comprehensively and effectively reflect the real opinions of the GSCM practitioners and maintain the integrity of the original evaluation information as well.
- There is no investigation on GSCM practices using the classic VIKOR method in multi-granularity extended probabilistic linguistic environment. Hence, this paper first

introduces the VIKOR method to MGEPLTSs environment, to propose a novel integrated best–worst and VIKOR methods with MGEPLTSs environment, and use this technique to assess green practices, such as obtaining the optimal green supplier in GSCM practices.

- The proposed approach provides an integration of various criteria on the basis of previous literature review, so we can have a clear and deep understanding on the critical success factors affecting GSCM practices. Meanwhile, in practice, organizations or departments can comprehend and benefit from the relevant, dependable and proven criteria according to the practices of case enterprises. These criteria can be applied as the benchmarking and improvement tools that in this case can reconcile the proven aspects on the environmental practices.

The rest of this paper is organized as follows. Section "Preliminaries" introduces the PLTSs and transformation functions for multi-granularity linguistic terms. Section "A new multi-granularity extended probabilistic linguistic term sets" proposes a multi-granularity extended probabilistic linguistic term sets. Section "Proposed methodology" introduces a novel integrated approach based on best–worst and VIKOR methods under multi-granularity extended probabilistic linguistic environment to solve GSS problems. A GSS case on GSCM practices is used to illustrate the feasibility of the proposed approach in Section "An illustrative example", and the sensitivity analysis and comparative analysis of results by our proposed approach is presented in this section. Finally, Section "Conclusions and future directions" presents the conclusions of this paper.

Preliminaries

In this section, we review some definitions related to the probabilistic linguistic term sets and multi-granularity linguistic terms.

Probabilistic linguistic term sets

PLTSs are the linguistic term sets composed of the linguistic term and the probability corresponding to the linguistic term and are used to express the evaluation information [30]. Nowadays, the relevant studies on the PLTSs have gradually attracted more and more attention from many scholars, and the PLTSs have been used in various situations. The relevant definitions of PLTSs are shown as follows [13, 60].

Definition 1. Let $S = \{s_0, \ldots, s_\tau\}$ be a linguistic term set, a probabilistic linguistic term set can be defined as follows:

$$L(p) = \left\{ L^{(k)}\left(p^{(k)}\right) \middle| L^{(k)} \in S,\ p^{(k)} \geq 0,\ k = 1,\ 2,\ \ldots,\ \#L(p),\ \sum_{k=1}^{\#L(p)} p^{(k)} \leq 1 \right\}, \tag{1}$$

where s_τ represents a possible value for a linguistic variable. $L^{(k)}(p^{(k)})$ is $L^{(k)}$ associated with the probability $p^{(k)}$, and $\#L(p)$ is the number of linguistic terms.

Definition 2. Given a PLTS $L^{(k)}(p^{(k)})$ with $\sum_{k=1}^{\#L(p)} p^{(k)} < 1$, it needs to be normalized as follows:

$$\overline{L}(p) = \left\{ L^{(k)}\left(\overline{p}^{(k)}\right) \middle| k = 1,\ 2,\ \ldots,\ \#L(p) \right\} \tag{2}$$

where $\overline{p}^{(k)} = p^{(k)} / \sum_{k=1}^{\#L(p)} p^{(k)}$.

Definition 3. If $\#L_1(p) > \#L_2(p)$, then we will add $\#L_1(p) - \#L_2(p)$ linguistic terms to $L_2(p)$ so that the number of linguistic terms in $\#L_1(p)$ and $\#L_2(p)$ is the same. The added linguistic terms are the smallest ones in $L_2(p)$, and the probabilities of all the linguistic terms are zero.

Multi-granularity linguistic terms

Since decision-makers have differences in cognition and evaluation conditions, to fully consider these differences, different granularity linguistic labels should be given for decision-makers to choose in the process of group decision-making. Then, preference information of different granularities needs to be transformed into the same granularity before aggregating preference information. Commonly, the most frequently used linguistic label is considered the basis set [11, 23, 52].

Definition 4. Let $S_\alpha^{(\psi)}$ and $S_\beta^{(\varphi)}$ be two linguistic terms with different granularities ψ and φ. If $S_\alpha^{(\psi)}$ should be transferred into the linguistic term with the same granularity as $S_\beta^{(\varphi)}$, then the transformation functions are defined as:

$$\begin{aligned} &F : S_\alpha^{(\psi)} \rightarrow S_\beta^{(\varphi)}, \\ &\alpha' = F(\alpha) = \alpha \frac{\varphi - 1}{\psi - 1}. \end{aligned} \tag{3}$$

A new multi-granularity extended probabilistic linguistic term sets

During the practical evaluation process, the sum of probability distributions among probabilistic linguistic elements may be greater than 1, because some decision-makers give hesitant fuzzy linguistic elements [14, 55]. For example, three decision-makers described the green product cost of the green supplies using $S^5 = \{s_0 = \text{very low}, s_1 = \text{low}, s_2 = \text{fair}, s_3 = \text{high}, s_4 = \text{very high}\}$. Therefore, if three decision-makers think that the response timeliness was fair, between fair and high, and high, respectively, then the probability distribution of linguistic terms is $\{s_2^5(0.67), s_3^5(0.67)\}$. This paradoxical situation is very common in daily life, so a standardized method should be adopted to deal with this kind of situation. Meanwhile, in group decision-making, decision-makers with different educational backgrounds and expression habits often choose linguistic sets with different granularities when giving evaluation information of green supplies. Therefore, this section proposes a new MGEPLTSs to represent the evaluation information. The relevant definitions of the MGEPLTSs are expressed as follows.

Definition 5. Let $S = \{s_0, \ldots, s_\tau\}$ be a linguistic term set, an extended probabilistic linguistic term set can be defined as:

$$\tilde{L}(p) = \left\{ \tilde{L}^{(k)}\left(p^{(k)}\right) \middle| \tilde{L}^{(k)} \in S,\ p^{(k)} \geq 0, \times k = 1,\ 2, \ldots, \#\tilde{L}(p) \right\}, \tag{4}$$

where $\tilde{L}^{(k)}(p^{(k)})$ is $\tilde{L}^{(k)}$ associated with the probability $p^{(k)}$, and $\#\tilde{L}(p)$ is the number of linguistic terms.

When the linguistic term sets of different granularities appear, we unify the MGEPLTSs into linguistic term sets with the same granularity referring to Definition 4, as shown in Definition 6.

Definition 6. Let $\tilde{L}_\alpha^{(\psi)}$ and $\tilde{L}_\beta^{(\varphi)}$ be two extended probabilistic linguistic terms with different granularities. If $\tilde{L}_\alpha^{(\psi)}$ is transferred into the linguistic term with the same granularity as $\tilde{L}_\beta^{(\varphi)}$, the transformation functions are defined as:

$$\begin{aligned} &F : \tilde{L}_\alpha^{(\psi)} \to \tilde{L}_\beta^{(\varphi)}, \\ &\alpha' = F(\alpha) = \alpha \frac{\varphi - 1}{\psi - 1}. \end{aligned} \tag{5}$$

Definition 7. Given an extended probabilistic linguistic term set $\tilde{L}^{(k)}(p^{(k)})$ with $\sum_{k=1}^{\#\tilde{L}(p)} p^{(k)} \neq 1$, then it needs to be normalized as:

$$\overline{\tilde{L}}(p) = \left\{ \tilde{L}^{(k)}\left(\overline{p}^{(k)}\right) \middle| \tilde{L}^{(k)} \in S,\ \overline{p}^{(k)} \geq 0, \times k = 1,\ 2, \ldots, \#\tilde{L}(p) \right\}, \tag{6}$$

where $\overline{p}^{(k)} = p^{(k)} / \sum_{k=1}^{\#\tilde{L}(p)} p^{(k)}$.

Definition 8. If $\#\tilde{L}_1(p) > \#\tilde{L}_2(p)$, then we will add $\#\tilde{L}_1(p) - \#\tilde{L}_2(p)$ linguistic terms to $\tilde{L}_2(p)$, so that the numbers of linguistic terms $\tilde{L}_1(p)$ and $\tilde{L}_2(p)$ are identical. The added linguistic terms are the smallest ones in $\tilde{L}_2(p)$, and the probabilities of all the linguistic terms are zero.

Definition 9. Let $\tilde{L}(p) = \left\{ \tilde{L}^{(k)}(p^{(k)}) \middle| \tilde{L}^{(k)} \in S,\ p^{(k)} \geq 0, k = 1,\ 2, \ldots, \#\tilde{L}(p) \right\}$ be an extended probabilistic linguistic term, then the score of $\tilde{L}(p)$ is as follows:

$$E\left(\tilde{L}(p)\right) = S_{\overline{\alpha}}, \tag{7}$$

where $\overline{\alpha} = \sum_{k=1}^{\#\tilde{L}(p)} r^{(k)} p^{(k)} \Big/ \sum_{k=1}^{\#\tilde{L}(p)} p^{(k)}$, and $r^{(k)}$ is the subscript of linguistic term $\tilde{L}(p)$.

(1) If $E\left(\tilde{L}_1(p)\right) > E\left(\tilde{L}_2(p)\right)$, then $\tilde{L}_1(p) \succ \tilde{L}_2(p)$.
(2) If $E\left(\tilde{L}_1(p)\right) = E\left(\tilde{L}_2(p)\right)$, then $\tilde{L}_1(p) \sim \tilde{L}_2(p)$.
(3) If $E\left(\tilde{L}_1(p)\right) < E\left(\tilde{L}_2(p)\right)$, then $\tilde{L}_1(p) \prec \tilde{L}_2(p)$.

Definition 10. Let $\tilde{L}(p) = \left\{ \tilde{L}^{(k)}(p^{(k)}) \middle| \tilde{L}^{(k)} \in S,\ p^{(k)} \geq 0, k = 1,\ 2, \ldots, \#\tilde{L}(p) \right\}$ be an extended probabilistic linguistic term, then the deviation degree function of $\tilde{L}(p)$ is as follows:

$$\sigma\left(\tilde{L}(p)\right) = \left(\sum_{k=1}^{\#\tilde{L}(p)} \left(p^{(k)}\left(r^{(k)} - \overline{\alpha} \right) \right)^2 \right)^{1/2} \Bigg/ \sum_{k=1}^{\#\tilde{L}(p)} p^{(k)}. \tag{8}$$

For two extended probability linguistic term sets $\tilde{L}_1(p)$ and $\tilde{L}_2(p)$ with $E\left(\tilde{L}_1(p)\right) = E\left(\tilde{L}_2(p)\right)$:

(1) If $\sigma\left(\tilde{L}_1(p)\right) > \sigma\left(\tilde{L}_2(p)\right)$, then $\tilde{L}(p_1) \prec \tilde{L}(p_2)$.
(2) If $\sigma\left(\tilde{L}(p_1)\right) = \sigma\left(\tilde{L}(p_2)\right)$, then $\tilde{L}(p_1) \sim \tilde{L}(p_2)$.
(3) If $\sigma\left(\tilde{L}(p_1)\right) < \sigma\left(\tilde{L}(p_2)\right)$, then $\tilde{L}(p_1) \succ \tilde{L}(p_2)$.

Definition 11. Let $\tilde{L}_1(p) = \left\{ \tilde{L}_1^{(k)}(p_1^{(k)}) \middle| k = 1,\ 2, \cdots, \#\tilde{L}_1(p) \right\}$ and $\tilde{L}_2(p) = \left\{ \tilde{L}_2^{(k)}(p_2^{(k)}) \middle| k = 1,\ 2, \ldots, \#\tilde{L}_2(p) \right\}$ be two ordered extended probabilistic linguistic terms, where the linguistic terms $\tilde{L}^{(k)}(p^{(k)})\left(k = 1,\ 2, \ldots, \#\tilde{L}_2(p)\right)$ are arranged according to the values of $r^{(k)}p^{(k)}\left(k = 1,\ 2, \ldots, \#\tilde{L}_2(p)\right)$ in descending order, and $\#\tilde{L}_1(p) = \#\tilde{L}_2(p)$, then the deviation degree between $\tilde{L}_1(p)$ and $\tilde{L}_2(p)$ is as follows:

$$d\left(\tilde{L}_1(p),\ \tilde{L}_2(p)\right)=\sqrt{\sum_{k=1}^{\#\tilde{L}_1(p)}\left(p_1^{(k)}r_1^{(k)}-p_2^{(k)}r_2^{(k)}\right)^2\Big/\#\tilde{L}_1(p)}. \tag{9}$$

Definition 12. Let $D = \{D_1,\ D_2,\ \ldots,\ D_G\}$ be a set of decision-making panels with decision weights $(\lambda_1,\ \lambda_2,\ \ldots,\ \lambda_G)^T$ and $\sum_{g=1}^{G}\lambda_g = 1$, $\tilde{L}^g(p) = \left\{\tilde{L}^{g(k)}(p^{g(k)})\Big|\tilde{L}^{g(k)} \in S,\ g = 1,\ 2,\ \ldots,\ G\right\}$ be the extended probabilistic linguistic term by gth decision-making panel, then the overall probability linguistic set of the decision-making panels is as follows:

$$\tilde{L}^t(p) = \left\{\tilde{L}^{t(k)}(p^{t(k)})\Big|\tilde{L}^{g(k)} \in S,\ p^{t(k)} = \sum_{g=1}^{G}\lambda_g v^{t(k)},\ k = 1,\ 2,\ \ldots,\ \#\tilde{L}(p)\right\}, \tag{10}$$

where $v^{t(k)}$ represents the probability weight of the linguistic term $\tilde{L}^{g(k)}$ in $\tilde{L}^g(p)$, as follows:

$$v^{t(k)} = \begin{cases} p^{t(k)},\ \tilde{L}^{t(k)} \in \tilde{L}^{g(k)} \\ 0,\ \tilde{L}^{t(k)} \notin \tilde{L}^{g(k)} \end{cases}. \tag{11}$$

Proposed methodology

Aiming at the MAGDM problems in which attributes are complexity, the selection of alternatives is diversity, and decision-makers are risk averse, this section attempts to conduct a new MAGDM approach based on multi-granularity extended probabilistic linguistic best–worst and VIKOR methods, which integrates multi-granularity, extended probabilistic linguistic term sets, BWM and VIKOR method. The proposed methodology is described as follows. First, the relative parameters are expressed as follows. $A = \{A_1,\ A_2,\ \ldots,\ A_m\}$ be a set of alternatives (namely green supplies in GSCM practices). $C = \{C_1,\ C_2,\ \ldots,\ C_n\}$ be a set of attributes as evaluation indexes of alternatives, which can be divided in the benefit attribute and the cost attribute. And ω_j is the weight of attribute C_j, satisfying $\omega_j \in [0,\ 1]$ and $\sum_j^n \omega_j = 1$. $D = \{D_1,\ D_2,\ \ldots,\ D_G\}$ be a set of decision-making panels participating in alternative evaluation, in which each decision-making panel has several decision-makers, and the corresponding weight λ_g of the decision-making panel D_g satisfies $\sum_g^G \lambda_g = 1$.

The attribute weights are unknown and decision-makers are diversity. Therefore, there are three phases in the process of MAGDM, including determining the weights of the decision-making panels and attributes by the multi-granularity extended probabilistic linguistic BWM, describing alternative evaluation using MGEPLTSs, and ranking the alternatives using the multi-granularity extended probabilistic linguistic VIKOR approach. Figure 1 presents the framework of MAGDM depicted, and intuitively describes the details of how to use the multi-granularity extended probabilistic linguistic best–worst and extended VIKOR methods.

Determining the weights by multi-granularity extended probabilistic linguistic best–worst method

In most cases, both expert weights and attribute weights are partially or completely unknown, which requires appropriate methods to further determine the weights. We extend the traditional BWM to the MGEPLTSs to compute the weights [34]. The details of the multi-granularity extended probabilistic linguistic BWM are as follows:

(1) Determining the weights of decision-making panels

Step 1. Managing directors determine the best decision-making panel B and the worst decision-making panel W.

Step 2. Managing directors choose their preferred linguistic term set from multi- granularity and then use the form of extended probabilistic linguistic term $\tilde{L}(p)_{Bg}$ to evaluate its preference degree of the best attribute relative to other attributes. The obtained best-to-others vector is denoted as $A_B = \left(\tilde{L}(p)_{B1},\ \tilde{L}(p)_{B2},\ \ldots\tilde{L}(p)_{BG}\right)^T$. Next, managing directors evaluate its preference degree of each attribute over the worst attribute using the extended probabilistic linguistic term $\tilde{L}(p)_{gW}$. The obtained others-to-worst vector is denoted as $A_W = \left(\tilde{L}(p)_{1W},\ \tilde{L}(p)_{2W},\ \ldots\tilde{L}(p)_{gW}\right)^T$. Then, the extended probabilistic linguistic terms are normalized using Eq. (6). The optional multi-granularity linguistic term sets are as follows:

$$S^3 = \{s_0 = \text{equally important},\ s_1 = \text{obviously important},\ s_2 = \text{extremely important}\}$$

$$S^5 = \left\{\begin{array}{l} s_0 = \text{evequally important},\ s_1 = \text{slightly important},\ s_2 = \text{obviously important}, \\ s_3 = \text{strongly important},\ s_4 = \text{extremely important} \end{array}\right\}$$

$$S^7 = \left\{\begin{array}{l} s_0 = \text{evequally important},\ s_1 = \text{slightly important},\ s_2 = \text{modernately important},\ s_3 = \text{important}, \\ s_4 = \text{strongly important},\ s_5 = \text{very strongly important},\ s_6 = \text{extremely important} \end{array}\right\}$$

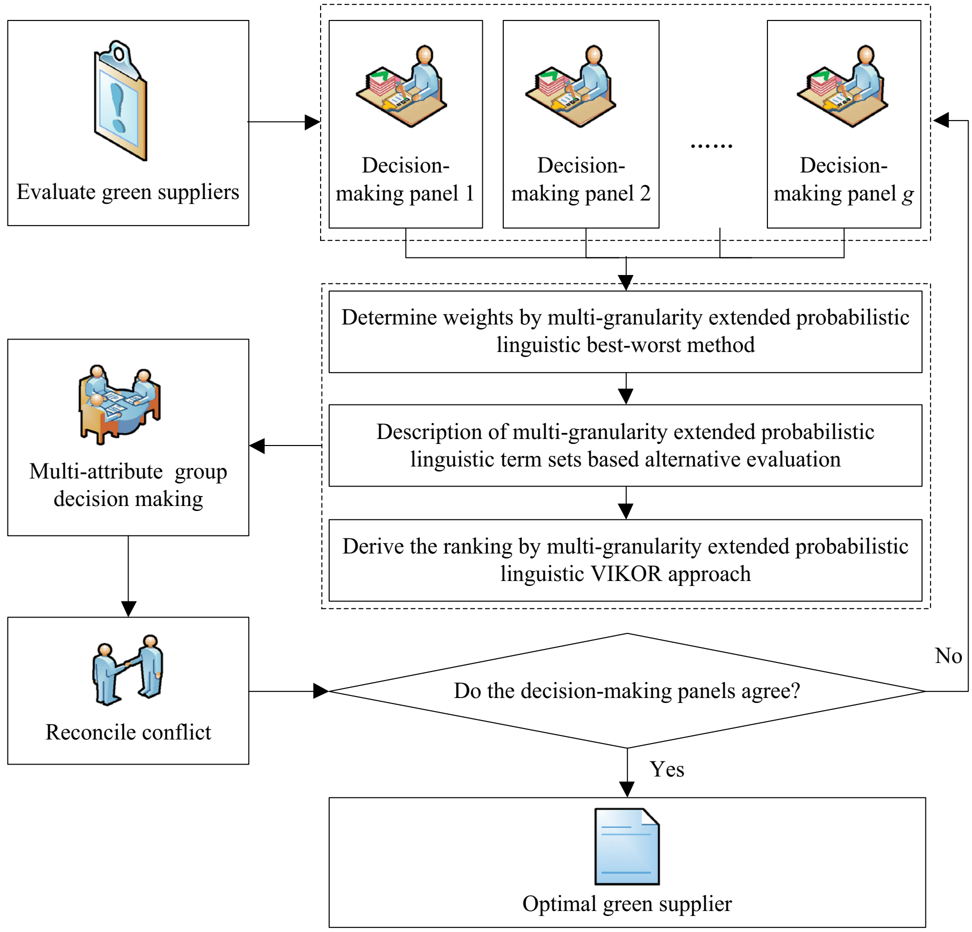

Fig. 1 The proposed MAGDM-based framework for green suppliers election

Step 3. Compute the optimal weights $(\lambda_1^*, \lambda_2^* \ldots, \lambda_g^*)$ of decision-making panels, which are computed such that the maximum absolute differences $\left|\frac{\omega_B}{\omega_g} - U\left(E\left(\tilde{L}(p)_{Bg}\right)\right)\right|$ and $\left|\frac{\omega_g}{\omega_W} - U\left(E\left(\tilde{L}(p)_{gW}\right)\right)\right|$ for all n are minimized, which can be built the fuzzy mathematical programming model:

$$\begin{aligned} &\min \delta \\ &s.t. \left|\frac{\lambda_B}{\lambda_g} - U\left(E\left(\tilde{L}(p)_{Bg}\right)\right)\right| \le \delta, \quad \text{for all } g \\ &\quad\;\; \left|\frac{\lambda_g}{\lambda_W} - U\left(E\left(\tilde{L}(p)_{gW}\right)\right)\right| \le \delta, \quad \text{for all } g \\ &\quad\;\; g = 1, 2, \ldots G, \end{aligned} \tag{12}$$

where $U\left(E\left(\tilde{L}(p)_{Bg}\right)\right) = \ell^{\#\tilde{L}(p)\cdot E\left(\tilde{L}(p)_{Bg}\right)/\tau}$ and $U\left(E\left(\tilde{L}(p)_{gW}\right)\right) = \ell^{\#\tilde{L}(p)\cdot E\left(\tilde{L}(p)_{gW}\right)/\tau}$ represent the utility values of cognitive linguistic evaluations $\tilde{L}(p)_{Bg}$ and $\tilde{L}(p)_{gW}$, $\ell = \sqrt[\#\tilde{L}(p)]{\text{Best/Worst}}$ represents the objective importance ratio of two adjacent linguistic terms, and Best / Worst is the maximum difference in the evaluation information of decision-making panel [24].

By solving the model, we obtain the $(\lambda_1^*, \lambda_2^* \ldots, \lambda_G^*)$ and δ. δ can measure of the consistency level of decision-making and its value close to zero shows a high consistency level.

(2) Determining the weights of attribute

Step 1. Decision-making panel D_g determines the best attribute B and the worst attribute W.

Step 2. Decision-making panel D_g chooses its preferred linguistic term set from multi- granularity and then uses the form of extended probabilistic linguistic term $\tilde{L}(p)_{Bj}$ to evaluate its preference degree of the best attribute relative to other attributes. The obtained best-to-others vector is denoted as $A_B^g = \left(\tilde{L}(p)_{B1}, \tilde{L}(p)_{B2}, \ldots \tilde{L}(p)_{Bn}\right)^T$. Next, decision-making panel D_g evaluates its preference degree of each attribute over the worst attribute using the extended probabilistic linguistic term $\tilde{L}(p)_{jW}$. The obtained others-to-worst vector is denoted as $A_W^g = \left(\tilde{L}(p)_{1W}, \tilde{L}(p)_{2W}, \ldots \tilde{L}(p)_{nW}\right)^T$. The optional multi-granularity linguistic term sets are the same as Step 2 in Section "Determining the weights by multi-granularity extended probabilistic linguistic best–worst method". Then, the multi-granularity linguistic terms are transformed into the same granularity using Eq. (5), and the extended probabilistic linguistic terms are normalized using Eq. (6).

Step 3. Compute the optimal attribute weights (ω_1^*, $\omega_2^* \ldots, \omega_n^*$), which are computed such that the maximum absolute differences $\left|\frac{\omega_B}{\omega_j} - U\left(E\left(\tilde{L}(p)_{Bj}\right)\right)\right|$ and $\left|\frac{\omega_j}{\omega_W} - U\left(E\left(\tilde{L}(p)_{jW}\right)\right)\right|$ for all n are minimized, which can be built the fuzzy mathematical programming model:

$$\begin{aligned}
&\min \sum_{g}^{G} \lambda_g \varepsilon_g \\
&s.t. \left|\frac{\omega_B}{\omega_j} - U\left(E\left(\tilde{L}(p)_{Bj}\right)\right)\right| \le \varepsilon_j, \text{ for all } j, \text{ for all } g \\
&\quad \left|\frac{\omega_j}{\omega_W} - U\left(E\left(\tilde{L}(p)_{jW}\right)\right)\right| \le \varepsilon_j, \text{ for all } j, \text{ for all } g \\
&\quad \sum_{j}^{n} \omega_j = 1 \\
&\quad j = 1, 2, \ldots n \\
&\quad \sum_{g}^{G} \lambda_g = 1 \\
&\quad g = 1, 2, \ldots G
\end{aligned} \tag{13}$$

where λ_g represents the weight of D_g, $U\left(E\left(\tilde{L}(p)_{Bj}\right)\right) = \ell^{\#\tilde{L}(p)\cdot E\left(\tilde{L}(p)_{Bj}\right)/\tau}$ and $U\left(E\left(\tilde{L}(p)_{jW}\right)\right) = \ell^{\#\tilde{L}(p)\cdot E\left(\tilde{L}(p)_{jW}\right)/\tau}$ represent the utility values of cognitive linguistic evaluations $\tilde{L}(p)_{Bj}$ and $\tilde{L}(p)_{jW}$, $\ell = \sqrt[\#\tilde{L}(p)]{\text{Best/Worst}}$ represents the objective importance ratio of two adjacent linguistic terms, and *Best* / *Worst* is the maximum difference in the evaluation information of decision-making panel [24].

By solving the model, we obtain the $\left(\omega_1^*, \omega_2^* \ldots, \omega_n^*\right)$ and $(\varepsilon_1, \varepsilon_2 \ldots, \varepsilon_G)$. $\sum_g^G \lambda_g \varepsilon_g$ can measure of the consistency level of decision-making and its value close to zero shows a high consistency level.

Description of multi-granularity extended probabilistic linguistic term sets based alternative evaluation

In the inspiration of PLTSs, we extend new MGEPLTSs to quantify preferences given by decision-makers to carry out alternative evaluation, which can comprehensively reflect the real opinions of decision-makers, and maintain the integrity of the original evaluation information as well. Each decision-making panel uses the MGEPLTSs to conduct the evaluation of alternatives. The optional multi-granularity linguistic term sets are the same as Step 2 in Section "Determining the weights by multi-granularity extended probabilistic linguistic best–worst method".

Step 1. Decision-making panel D_g chooses a preferred linguistic term set from multi-granularity and evaluates the alternative A_i regarding attribute C_j through MGEPLTSs; here, it is written as $\tilde{L}_{ij}^{D_g}(p)$.

$$\begin{aligned}
&\overline{S}^3 = \{s_0 = \text{low}, \ s_1 = \text{fair}, \ s_2 = \text{high}\} \\
&\overline{S}^5 = \{s_0 = \text{very low}, \ s_1 = \text{low}, \ s_2 = \text{fair}, \\
&s_3 = \text{high}, s_4 = \text{very high}\} \\
&\overline{S}^7 = \{s_0 = \text{very low}, \ s_1 = \text{low}, \ s_2 = \text{moderately low}, \\
&s_3 = \text{fair}, \ s_4 = \text{moderately high}, \\
&s_5 = \text{high}, \ s_6 = \text{very high}\}.
\end{aligned}$$

Step 2. We transform multi-granularity linguistic terms into the same granularity using Eq. (5) and normalize extended probabilistic linguistic terms using Eq. (6).

Step 3. According to Eqs. (10) and (11), for alternative A_i, its evaluation can be determined as follows:

$$\begin{aligned}
E^{A_i} = &\sum_{g=1}^{G} \lambda_g \cdot \tilde{L}_{ij}^{D_g}(p), (i = 1, 2, \cdots m, \\
&j = 1, 2, \cdots n, g = 1, 2, \cdots G).
\end{aligned} \tag{14}$$

Thereby, we obtain the overall probabilistic linguistic decision-making matrix of decision-making panels shown in Table 1.

Deriving the ranking by multi-granularity extended probabilistic linguistic VIKOR method

Because the decision-makers need to respond to various situations, we proposed multi-granularity extended probabilistic linguistic VIKOR method to obtain the ranking of alternatives. The details of the proposed approach are as follows. Through the alternatives evaluation in Section "Description of multi-granularity extended probabilistic linguistic term sets based alternative evaluation", the overall probabilistic linguistic decision-making matrix of decision-making panels is constructed and shown in Table 1.

Definition 13. Let $R = \left[\tilde{L}_{ij}(p)\right]_{m \times n}$ be a probabilistic linguistic decision-making matrix of alternatives, then the vector of attribute values of the alternative A_i can be defined as $\tilde{L}_i(p) = \left\{\tilde{L}_{i1}(p), \ \tilde{L}_{i2}(p), \ldots, \ \tilde{L}_{in}(p)\right\}$.

Table 1 The overall probabilistic linguistic decision-making matrix of decision-making panels

E	C_1	$\cdots$	C_j	$\cdots$	C_n
A_1	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{11}^{D_g}(p)$	$\cdots$	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{1j}^{D_g}(p)$	$\cdots$	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{1n}^{D_g}(p)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
A_i	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{i1}^{D_g}(p)$	$\cdots$	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{ij}^{D_g}(p)$	$\cdots$	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{in}^{D_g}(p)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
A_m	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{m1}^{D_g}(p)$	$\cdots$	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{mj}^{D_g}(p)$	$\cdots$	$\sum_{g=1}^{G}\lambda_g\cdot\tilde{L}_{mn}^{D_g}(p)$

Definition 14. Let $R = \left[\tilde{L}_{ij}(p)\right]_{m\times n}$ be a probabilistic linguistic decision-making matrix of alternatives, then the positive ideal solution $\tilde{L}^{+}(p)$ and the negative ideal solution $\tilde{L}^{-}(p)$ of alternative can be defined as:

$$\begin{aligned}\tilde{L}^{+}(p) &= \left\{\tilde{L}_1^{+}(p),\ \tilde{L}_2^{+}(p),\ \ldots,\ \tilde{L}_n^{+}(p)\right\}\\ &= \left\{\left(\mathrm{m}\,a\,x\tilde{L}(p)\,|\,j\in I\right),\ \left(\mathrm{m}\,i\,n\tilde{L}(p)\big|\,j\in I^{*}\right)\right\}\\ &\quad (j=1,\ 2,\ \ldots,\ n)\\ \tilde{L}^{-}(p) &= \left\{\tilde{L}_1^{-}(p),\ \tilde{L}_2^{-}(p),\ \ldots,\ \tilde{L}_n^{-}(p)\right\}\\ &= \left\{\left(\mathrm{m}\,i\,n\tilde{L}(p)\,|\,j\in I\right),\ \left(\mathrm{m}\,a\,x\tilde{L}(p)\big|\,j\in I^{*}\right)\right\}\\ &\quad (j=1,\ 2,\ \ldots,\ n),\end{aligned} \tag{15}$$

where I is the benefit attribute, and I^{*} is the cost attribute.

Definition 15. The group utility measure of alternative A_i can be denoted as follows:

$$\begin{aligned}S_i &= \sum_{j=1}^{n}\omega_j\frac{d\left(\tilde{L}_j^{+}(p),\ \tilde{L}_{ij}(p)\right)}{d\left(\tilde{L}_j^{+}(p),\ \tilde{L}_j^{-}(p)\right)}\\ &= \sum_{j=1}^{n}\omega_j\frac{\sqrt{\sum_{k=1}^{\#\tilde{L}_{ij}(p)}\left(\left(p_j^{(k)}r_j^{(k)}\right)^{+}-p_{ij}^{(k)}r_{ij}^{(k)}\right)^2\Big/\#\tilde{L}_{ij}(p)}}{\sqrt{\sum_{k=1}^{\#\tilde{L}_{ij}(p)}\left(\left(p_j^{(k)}r_j^{(k)}\right)^{+}-\left(p_j^{(k)}r_j^{(k)}\right)^{-}\right)^2\Big/\#\tilde{L}_{ij}(p)}}.\end{aligned} \tag{16}$$

Definition 16. The individual regret measure of alternative A_i can be denoted as follows:

$$\begin{aligned}R_i &= \max_j\left(\omega_j\frac{d\left(\tilde{L}_j^{+}(p),\ \tilde{L}_{ij}(p)\right)}{d\left(\tilde{L}_j^{+}(p),\ \tilde{L}_j^{-}(p)\right)}\right)\\ &= \max_j\left(\omega_j\frac{\sqrt{\sum_{k=1}^{\#\tilde{L}_{ij}(p)}\left(\left(p_j^{(k)}r_j^{(k)}\right)^{+}-p_{ij}^{(k)}r_{ij}^{(k)}\right)^2\Big/\#\tilde{L}_{ij}(p)}}{\sqrt{\sum_{k=1}^{\#\tilde{L}_{ij}(p)}\left(\left(p_j^{(k)}r_j^{(k)}\right)^{+}-\left(p_j^{(k)}r_j^{(k)}\right)^{-}\right)^2\Big/\#\tilde{L}_{ij}(p)}}\right).\end{aligned} \tag{17}$$

Definition 17. The compromise measure of alternative A_i can be denoted as follows:

$$Q_i = \alpha\frac{S_i - S^{-}}{S^{+}-S^{-}} + (1-\alpha)\frac{R_i - R^{-}}{R^{+}-R^{-}}, \tag{18}$$

where $S^{+} = \max_i(S_i)$, $S^{-} = \min_i(S_i)$, $R^{+} = \max_i(R_i)$, $R^{-} = \min_i(R_i)$, and $\alpha \in (0,\ 1)$ represents a control parameter. Q_i can be used to balance the group utility measure and individual regret measure by changing the value of α.

Rank the alternatives based on Q_i values. The smaller the Q_i value, the better the alternative A_i. At the same time, Q_i values satisfy the following two conditions:

(1) Acceptable advantage: $Q_i^{(2)} - Q_i^{(1)} \geq 1\big/(m-1)$, where $Q_i^{(2)}$ is with the second-smallest Q value, $Q_i^{(1)}$ is with the smallest Q value, and m is the number of alternatives.
(2) Acceptable stability: the alternative of $Q_i^{(1)}$ should also be the best ranked by S_i and R_i, which indicates that this compromise solution is stable. If one of these two conditions is not satisfied, compromise solutions could be obtained:

If condition (1) is not satisfied, $A_i^{(m)}$ is determined by the relationship $Q_i^{(m)} - Q_i^{(1)} \leq 1\big/(m-1)$ for the maximum m, and all alternatives are compromise solutions. If Condition (2) is not satisfied, then alternatives $A_i^{(1)}$ and $A_i^{(2)}$ are both compromise solutions.

Table 2 The major attributes of green supplier selection

Attributes	Description	References
Green product cost C_1	A measure of the cost paid by suppliers. It includes the design, manufacture, packaging, stockpiling, transportation, repair, recycle, and so on	[7, 12, 15, 32, 53]
Green technology capability C_2	It aims to promote sustainable economic development and includes green energy, green manufacturing, green management, etc	[7, 15, 25, 28, 32, 53, 54]
Product quality management C_3	We measure supplier control service and product quality. Including advanced management ideas, perfect product quality and good post sale service	[7, 15, 32, 53, 54]
Environmental pollution of production C_4	It represents the supplier's pollution per time unit and includes harmful materials, random discharge of sewage, disorderly emissions, and so on	[7, 9, 15, 17, 19, 25, 32, 53]
Corporate social responsibility C_5	Including labor relations, human rights and interests of employees, comply with local regulations and policies	[7, 9, 12, 15, 19, 37, 40]

An illustrative example

In this section, an illustrative case study is conducted to present the application of the novel integrated best–worst and VIKOR methods under multi-granularity extended probabilistic linguistic environment for green supplier selection problems.

Problem description

With the continuous development of agriculture and industry, the world's natural environment is worsening. The green economy provides a new mode for simultaneous economic development and environmental protection. GSS is one of the most important activities in the modern manufacturing industry to reflect the development potential and competitiveness of an enterprise in the long run. Consider a home furnishing enterprise seeking a green supplier to purchase product assemblies. During the selection process, five major attributes $C = \{C_1, C_2, C_3, C_4, C_5\}$ are considered through green economic aspects, literature review and discussion with experts who have vast knowledge and experience in green supply chain and environmental management systems, as shown in Table 2.

- *Green product cost and product quality management* The cost, quality, and service have been widely considered as effective factors in the traditional supplier selection problems. During the selection process of the performance evaluation indicators of GSS, Wu et al. [53] considered seven major perspectives according to green economic aspects: green product innovation, environmental regime, use of green technology, product quality management, total green product cost, resource consumption, and environmental pollution of production,and identified quality, delivery, price/cost, manufacturing capability, service, management, and technology. What is more, Govindan et al. [15] considered five major perspectives: cost, quality, technology, environmental impacts and technology capability. Therefore, we determined the green product cost C_1 and product quality management C_3.
- *Green technology capability* The development of infrastructure, green energy, green manufacturing and green management will improve the green supply chain of the industry and promote sustainable economic development. Ecer [12] indicate that the most important factors that are effective in selecting green suppliers are cleaner production, energy/material saving, green package, remanufacturing, and environmental management system. In the selection process of the performance evaluation indicators of GSS, Qin et al. [32] considered ten criteria, among which green product innovation, use of environmentally friendly technology, resource consumption, environment management, and quality management are

Table 3 The best-to-others vector and others-to-worst vector with respect to decision-making panels

The best decision-making panel	The worst decision-making panel	A_B/A_W	D_1	D_2	D_3
D_3	D_1	A_B	$\{s_2^5(0.4),\ s_3^5(0.8)\}$	$\{s_1^5(0.4),\ s_2^5(0.6)\}$	$\{s_0^5(1.0)\}$
		A_W	$\{s_0^5(1.0)\}$	$\{s_1^5(0.8),\ s_2^5(0.2)\}$	$\{s_2^5(0.6),\ s_3^5(0.6)\}$

Table 4 The best-to-others vector and others-to-best vector with respect to evaluation attributes

A_B^j/A_W^j	C_1	C_2	C_3	C_4	C_5
A_B^1	$\{s_3^5(0.2),\ s_4^5(0.8)\}$	$\{s_0^5(1.0)\}$	$\{s_3^5(0.6),\ s_4^5(0.6)\}$	$\{s_1^5(0.8)\}$	$\{s_2^5(0.6),\ s_3^5(0.4)\}$
A_W^1	$\{s_0^5(1.0)\}$	$\{s_3^5(0.2),\ s_4^5(0.8)\}$	$\{s_1^5(0.6),\ s_2^5(0.4)\}$	$\{s_2^5(0.4),\ s_3^5(0.8)\}$	$\{s_1^5(0.6),\ s_2^5(0.4)\}$
A_B^2	$\{s_3^7(0.8)\}$	$\{s_1^7(0.4),\ s_2^7(0.6)\}$	$\{s_1^7(0.6),\ s_2^7(0.6)\}$	$\{s_0^7(1.0)\}$	$\{s_2^7(0.2),\ s_3^7(0.8)\}$
A_W^2	$\{s_0^7(1.0)\}$	$\{s_2^7(0.4),\ s_3^7(0.6)\}$	$\{s_2^7(0.8),\ s_3^7(0.2)\}$	$\{s_3^7(0.8)\}$	$\{s_1^7(0.4),\ s_2^7(0.8)\}$
A_B^3	$\{s_3^5(0.6),\ s_4^5(0.4)\}$	$\{s_0^5(1.0)\}$	$\{s_2^5(0.8),\ s_3^5(0.4)\}$	$\{s_1^5(0.8),\ s_2^5(0.2)\}$	$\{s_4^5(0.8)\}$
A_W^3	$\{s_1^5(0.6),\ s_2^5(0.4)\}$	$\{s_4^5(0.8)\}$	$\{s_2^5(1.0)\}$	$\{s_2^5(0.6),\ s_3^5(0.6)\}$	$\{s_0^5(1.0)\}$

more important. Hence, we determined the green technology capability C_2.

- *Environmental pollution of production and corporate social responsibility* In the recent purchasing decisions under GSCM, incorporation of objective environmental criteria in the evaluation systems ensures better environmental performance in the collaborative supply chains. Lahri et al. [19] proposed a two-stage multi-objective possibilistic integer linear programming sustainable supply chain network design model, minimizing the economic, environmental goals and maximizing the social sustainability goals. Samda et al. [37, 40] indicated that the GSCM and the firms' environmental, operational and economic performances were found to be positively and significantly associated. Demir et al. [9] pointed out that depleting natural resources and limited amount of landfill areas have forced many governments to impose stricter measures on environmental performance. In order to comply with those measures and to have a better environmental image, companies are investing heavily in environmental, social and economic responsibility issues. Moreover, they continuously track the environmental performance of their suppliers. Thus, it is the responsibility of the industry to develop and implement a management system for measuring safety by analysis and prevention of physical, chemical, and organic hazards throughout the whole operation of the industry. Consequently, we determined the environmental pollution of production C_4 and corporate social responsibility C_5.

According to the procurement needs of enterprises and the requirements of green suppliers, trade representative in China needs to conduct a detailed investigation on suppliers in North China, South China and Central China. After preliminary screening, the enterprise will assess four potential suppliers $A = \{A_1,\ A_2,\ A_3,\ A_4\}$. It is necessary to select the green supplier that best meets the company's needs as a long-term partner. The trade representative will convene procurement specialists from North China, South China and Central China to form three decision-making panels, namely the decision-making panel from North China D_1, the decision-making panel from South China D_2 and the decision-making panel from Central China D_3, each of which is composed of 5 procurement specialists. They evaluate four green suppliers according to the five major attributes of green supplier selection.

Implementation and results

(1) Determining the weights of decision-making panels

Through the understanding of the three decision-making teams, the trade representatives can learn that the authority of each decision-making team is different. Therefore, the weights of decision-making panels are calculated by the proposed multi-granularity extended probabilistic linguistic best–worst method.

The trade representatives choose their preferred linguistic term set from multi-granularity and use the form of extended probabilistic linguistic term to obtain best-to-others vector and others-to-worst vector concerning decision-making panels, as displayed in Table 3. The trade representatives choose the linguistic term set with granularity 5, S^5.

Then, the extended probabilistic linguistic terms are normalized using Eq. (6). According to Eq. (12), the optimization model for weights of decision-making panels is established as follows:

$$\begin{aligned}
&\min \delta \\
&s.t. \left|\frac{\lambda_3}{\lambda_1} - 4^{E\left(\tilde{L}(p)_{31}\right)/4}\right| \le \delta,\ \left|\frac{\lambda_3}{\lambda_2} - 4^{E\left(\tilde{L}(p)_{32}\right)/4}\right| \le \delta \\
&\left|\frac{\lambda_2}{\lambda_1} - 4^{E\left(\tilde{L}(p)_{21}\right)/4}\right| \le \delta,\ \left|\frac{\lambda_3}{\lambda_1} - 4^{E\left(\tilde{L}(p)_{31}\right)/4}\right| \le \delta.
\end{aligned}$$

By solving above model, $\delta = 0.0826$ can be obtained. The optimal weight vector of decision-making panels is $\left(\lambda_1^*, \lambda_2^*, \lambda_3^*\right)^T = (0.1662,\ 0.3506, 0.4832)^T$.

(2) The determination of attribute weights

The attribute weights are calculated by the proposed multi-granularity extended probabilistic linguistic BWM. The best indexes determined by the three decision-making panels are C_2, C_4 and C_2, respectively, and the worst indexes are C_1, C_1 and C_5, respectively. Three decision-making panels choose their preferred linguistic term set from multi-granularity, and then use the form of extended probabilistic linguistic term to obtain best-to-others vector and others-to-worst vector concerning evaluation attributes, as displayed in Table 4. Among them, D_1 and D_3 choose the linguistic term set with granularity 5, S^5; D_2 chooses the linguistic term set with granularity 7, S^7.

Then, the multi-granularity linguistic terms are transformed into the same granularity using Eq. (5) and the extended probabilistic linguistic terms are normalized using Eq. (6). Based on Eq. (13), the optimization model of attribute weights is established as follows:

$$\begin{aligned}
&\min 0.1662\varepsilon_1 + 0.3506\varepsilon_2 + 0.4832\varepsilon_3 \\
&s.t. \left|\frac{\omega_2}{\omega_1} - 4^{E\left(\tilde{L}(p)_{21}\right)/4}\right| \le \varepsilon_1,\ \left|\frac{\omega_2}{\omega_3} - 4^{E\left(\tilde{L}(p)_{23}\right)/4}\right| \le \varepsilon_1, \\
&\left|\frac{\omega_2}{\omega_4} - 4^{E\left(\tilde{L}(p)_{24}\right)/4}\right| \le \varepsilon_1,\ \left|\frac{\omega_2}{\omega_5} - 4^{E\left(\tilde{L}(p)_{25}\right)/4}\right| \le \varepsilon_1 \\
&\left|\frac{\omega_3}{\omega_1} - 4^{E\left(\tilde{L}(p)_{31}\right)/4}\right| \le \varepsilon_1, \\
&\left|\frac{\omega_4}{\omega_1} - 4^{E\left(\tilde{L}(p)_{41}\right)/4}\right| \le \varepsilon_1,\ \left|\frac{\omega_5}{\omega_1} - 4^{E\left(\tilde{L}(p)_{51}\right)/4}\right| \le \varepsilon_1 \\
&\left|\frac{\omega_4}{\omega_1} - 3^{E\left(\tilde{L}(p)_{41}\right)/4}\right| \le \varepsilon_2,\ \left|\frac{\omega_4}{\omega_2} - 3^{E\left(\tilde{L}(p)_{42}\right)/4}\right| \le \varepsilon_2, \\
&\left|\frac{\omega_4}{\omega_3} - 3^{E\left(\tilde{L}(p)_{43}\right)/4}\right| \le \varepsilon_2,\ \left|\frac{\omega_4}{\omega_5} - 3^{E\left(\tilde{L}(p)_{45}\right)/4}\right| \le \varepsilon_2 \\
&\left|\frac{\omega_2}{\omega_1} - 3^{E\left(\tilde{L}(p)_{21}\right)/4}\right| \le \varepsilon_2, \\
&\left|\frac{\omega_3}{\omega_1} - 3^{E\left(\tilde{L}(p)_{31}\right)/4}\right| \le \varepsilon_2,\ \left|\frac{\omega_5}{\omega_1} - 3^{E\left(\tilde{L}(p)_{51}\right)/4}\right| \le \varepsilon_2 \\
&\left|\frac{\omega_2}{\omega_1} - 4^{E\left(\tilde{L}(p)_{21}\right)/4}\right| \le \varepsilon_3, \\
&\left|\frac{\omega_2}{\omega_3} - 4^{E\left(\tilde{L}(p)_{23}\right)/4}\right| \le \varepsilon_3,\ \left|\frac{\omega_2}{\omega_4} - 4^{E\left(\tilde{L}(p)_{24}\right)/4}\right| \le \varepsilon_3, \\
&\left|\frac{\omega_2}{\omega_5} - 4^{E\left(\tilde{L}(p)_{25}\right)/4}\right| \le \varepsilon_3 \\
&\left|\frac{\omega_1}{\omega_5} - 4^{E\left(\tilde{L}(p)_{15}\right)/4}\right| \le \varepsilon_3, \\
&\left|\frac{\omega_3}{\omega_5} - 4^{E\left(\tilde{L}(p)_{35}\right)/4}\right| \le \varepsilon_3,\ \left|\frac{\omega_4}{\omega_5} - 4^{E\left(\tilde{L}(p)_{45}\right)/4}\right| \le \varepsilon_3 \\
&\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 = 1
\end{aligned}$$

By solving above model, $\varepsilon_1 = 0.1802$, $\varepsilon_2 = 0.1061$, $\varepsilon_3 = 0.1263$ can be obtained. The optimal weight vector of attributes is $\left(\omega_1^*, \omega_2^*, \omega_3^*, \omega_4^*, \omega_5^*\right)^T = (0.1581, 0.3063, 0.1893, 0.2401, 0.1062)^T$.

(3) Alternative evaluation

The three decision-making panels choose their preferred linguistic term set from multi-granularity and evaluate alternative through the MGEPLTSs. The evaluation results are shown in Table 5. Among them, D_1 and D_3 choose the linguistic term set with granularity 5, S^5; D_2 chooses the linguistic term set with granularity 7, S^7.

The normalized multi-granularity extended probabilistic linguistic evaluation of alternatives is obtained using Eqs. (5) and (6). In addition, the overall probabilistic linguistic decision-making matrix of decision-making panels can be obtained using Eq. (14) shown in Table 6.

(4) The deriving of ranking

The ranking is calculated by the proposed multi-granularity extended probabilistic linguistic VIKOR approach.

Step 1. Based on alternative evaluation, we can obtain the probabilistic linguistic decision-making matrix of decision-making panels, as shown in Table 6.

Step 2. According to Eq. (15), we calculate the positive ideal solution $\tilde{L}^+(p)$ and the negative ideal solution $\tilde{L}^-(p)$ of alternative as follows:

$$\begin{aligned}
\tilde{L}^+(p) &= \left\{\tilde{L}_1^+(p),\ \tilde{L}_2^+(p), \tilde{L}_3^+(p), \tilde{L}_4^+(p), \tilde{L}_5^+(p)\right\} \\
&= \Big\{\left\{s_0^5(0.42),\ s_1^5(0.23),\ s_2^5(0.35)\right\}, \\
&\left\{s_3^5(0.28), s_{10/3}^5(0.35),\ s_4^5(0.37)\right\}, \\
&\left\{s_2^5(0.26), s_3^5(0.38), s_{10/3}^5(0.38),\ s_4^5(0.06)\right\}, \\
&\left\{s_1^5(0.60), s_{4/3}^5(0.30),\ s_2^5(0.10)\right\},
\end{aligned}$$

Table 5 The multi-granularity extended probabilistic linguistic evaluation of alternatives

A_m	D_j	C_1	C_2	C_3	C_4	C_5
A_1	D_1	$\{s_0^5(0.4),\ s_1^5(0.6)\}$	$\{s_3^5(0.6),\ s_4^5(0.6)\}$	$\{s_3^5(0.4),\ s_4^5(0.6)\}$	$\{s_1^5(0.8),\ s_2^5(0.2)\}$	$\{s_1^5(0.8)\}$
	D_2	$\{s_0^7(0.8),\ s_2^7(0.2)\}$	$\{s_5^7(0.2),\ s_6^7(0.8)\}$	$\{s_5^7(0.8)\}$	$\{s_2^7(1.0)\}$	$\{s_2^7(0.4),\ s_3^7(0.4)\}$
	D_3	$\{s_1^5(0.6),\ s_3^5(0.6)\}$	$\{s_3^5(0.4),\ s_4^5(0.6)\}$	$\{s_2^5(0.6),\ s_3^5(0.2)\}$	$\{s_1^5(0.8),\ s_2^5(0.2)\}$	$\{s_2^5(0.8)\}$
A_2	D_1	$\{s_2^5(0.8)\}$	$\{s_0^5(1.0)\}$	$\{s_2^5(0.8),\ s_3^5(0.2)\}$	$\{s_4^5(1.0)\}$	$\{s_3^5(0.2),\ s_4^5(0.8)\}$
	D_2	$\{s_3^7(0.4),\ s_4^7(0.4)\}$	$\{s_1^7(0.8),\ s_2^7(0.2)\}$	$\{s_3^7(0.8)\}$	$\{s_4^7(0.4),\ s_5^7(0.6)\}$	$\{s_5^7(0.4),\ s_6^7(0.6)\}$
	D_3	$\{s_2^5(0.8),\ s_3^5(0.2)\}$	$\{s_0^5(0.4),\ s_1^5(0.6)\}$	$\{s_0^5(0.4),\ s_1^5(0.6)\}$	$\{s_4^5(1.0)\}$	$\{s_3^5(0.2),\ s_4^5(0.8)\}$
A_3	D_1	$\{s_2^5(0.2),\ s_3^5(0.8)\}$	$\{s_3^5(1.0)\}$	$\{s_3^5(0.8),\ s_4^5(0.2)\}$	$\{s_2^5(0.6),\ s_3^5(0.2)\}$	$\{s_1^5(0.8)\}$
	D_2	$\{s_2^7(1.0)\}$	$\{s_5^7(1.0)\}$	$\{s_5^7(0.8)\}$	$\{s_1^7(0.2),\ s_3^7(0.8)\}$	$\{s_2^7(0.2),\ s_3^7(0.8)\}$
	D_3	$\{s_2^5(0.2),\ s_3^5(0.8)\}$	$\{s_3^5(0.8),\ s_4^5(0.2)\}$	$\{s_2^5(1.0)\}$	$\{s_2^5(0.2),\ s_3^5(0.8)\}$	$\{s_2^5(0.8)\}$
A_4	D_1	$\{s_0^5(0.2),\ s_1^5(0.8)\}$	$\{s_2^5(0.8)\}$	$\{s_2^5(0.8),\ s_3^5(0.2)\}$	$\{s_2^5(0.2),\ s_3^5(0.8)\}$	$\{s_3^5(1.0)\}$
	D_2	$\{s_3^7(1.0)\}$	$\{s_3^7(0.4),\ s_4^7(0.6)\}$	$\{s_3^7(1.0)\}$	$\{s_2^7(0.2),\ s_3^7(0.8)\}$	$\{s_3^7(0.2),\ s_5^7(0.8)\}$
	D_3	$\{s_0^5(0.8),\ s_1^5(0.2)\}$	$\{s_2^5(0.4),\ s_3^5(0.6)\}$	$\{s_1^5(0.8),\ s_2^5(0.2)\}$	$\{s_2^5(0.4),\ s_3^5(0.6)\}$	$\{s_3^5(0.8)\}$

$$\left\{s_3^5(0.12),\ s_{10/3}^5(0.12),\ s_4^5(0.76)\right\}\Big\}$$

$$\begin{aligned}\tilde{L}^-(p) &= \left\{\tilde{L}_1^-(p),\ \tilde{L}_2^-(p),\ \tilde{L}_3^-(p),\ \tilde{L}_4^-(p),\ \tilde{L}_5^-(p)\right\}\\ &= \Big\{\left\{s_{4/3}^5(0.35),\ s_2^5(0.13),\ s_3^5(0.52)\right\},\\ &\quad \left\{s_0^5(0.56),\ s_{2/3}^5(0.24),\ s_1^5(0.14),\ s_{4/3}^5(0.06)\right\},\\ &\quad \left\{s_1^5(0.22),\ s_2^5(0.72),\ s_3^5(0.06)\right\},\\ &\quad \left\{s_{8/3}^5(0.12),\ s_{10/3}^5(0.21),\ s_4^5(0.67)\right\},\\ &\quad \left\{s_1^5(0.35),\ s_{4/3}^5(0.15),\ s_2^5(0.50)\right\}\Big\}.\end{aligned}$$

Step 3. Calculate the group utility measure S_i and the individual regret measure R_i using Eqs. (16) and (17). The results are shown as follows:$S_1 = 0.3143$, $S_2 = 0.6572$, $S_3 = 0.6236$, $S_4 = 0.7262$; $R_1 = 0.1726$, $R_2 = 0.2163$, $R_3 = 1752$, $R_4 = 0.1898$.

Step 4. Calculate the compromise measure Q_i using Eq. (18), which $\alpha = 0.5$. The results are shown as follows:$Q_1 = 0.0034$, $Q_2 = 0.9312$, $Q_3 = 0.3566$, $Q_4 = 0.6671$.

Step 5. Rank the alternatives based on Q_i values. We find that Q_1 value is the smaller the of the alternative A_1. At the same time, Q_i values satisfy the following two conditions, namely $Q_3 - Q_1 = 0.3532 \leq 1\big/(4-1)$ and the alternative A_1 also be the best ranked by S_i and R_i. Thus, the optimal green supplier is A_1.

Sensitivity analysis

In this section, sensitivity analyses regarding different parameters and different standard granularities are conducted to examine their impacts on the decision-making results.

(1) The effect of α on the ranking

According to Eq. (17), we find that the control parameter α will affect the ranking result of alternatives. In practice, the parameter α is based on the decision-makers' preferences. Here, we use a value of α from 0 to 1 in increment of 0.1 to analyze the sensitivity. The compromise measure of alternative A_i under different values of α is shown in Fig. 2. As can be seen from Fig. 2, the ranking of alternatives is changed with the values of α. However, the best green supplier is always A_1; therefore, our proposed method is robust. Additionally, the ranking of A_2 improves as α increases, while the ranking of A_4 degrades as α increases, which reveals that the decision mechanisms affect the ranking result. In general, Fig. 2 illustrates the stability of our method in a simple and direct manner.

(2) The effect of standard granularity on the ranking

The probabilistic linguistic decision-making matrix of alternatives largely depends on the determination of the standard granularity. To explore the influence of different standard granularities on the results, the sensitivity analysis was carried out with granularity 7 as the standard granularity, and the compromise measure of different alternatives under different granularities is shown in Fig. 3. As can be seen from Fig. 3, whether the standard granularity is 5 or 7, Q_i of A_1 is always the minimum value and Q_i of A_2 is always the maximum value. Accordingly, if any multi-granularity is selected as the standard granularity, the decision information before and after conversion is equivalent and has slight effect on the comprehensive dominance and ranking result, which further shows the stability of the proposed approach.

Table 6 The overall probabilistic linguistic decision-making matrix of decision-making panels

A_m	C_1	C_2	C_3	C_4	C_5
A_1	$\left\{s_0^5(0.35), s_1^5(0.34), s_{4/3}^5(0.07), s_3^5(0.24)\right\}$	$\left\{s_3^5(0.28), s_{10/3}^5(0.35)\ s_4^5(0.37)\right\}$	$\left\{s_2^5(0.21), s_3^5(0.31), s_{10/3}^5(0.30), s_4^5(0.18)\right\}$	$\left\{s_1^5(0.60), s_{4/3}^5(0.30), s_2^5(0.10)\right\}$	$\left\{s_1^5(0.35), s_{4/3}^5(0.15), s_2^5(0.50)\right\}$
A_2	$\left\{s_2^5(0.78), s_{8/3}^5(0.18), s_3^5(0.10)\right\}$	$\left\{s_0^5(0.56), s_{2/3}^5(0.24), s_1^5(0.14), s_{4/3}^5(0.06)\right\}$	$\left\{s_0^5(0.10), s_1^5(0.30), s_2^5(0.54), s_3^5(0.06)\right\}$	$\left\{s_{8/3}^5(0.12), s_{10/3}^5(0.21), s_4^5(0.67)\right\}$	$\left\{s_3^5(0.12), s_{10/3}^5(0.12), s_4^5(0.76)\right\}$
A_3	$\left\{s_{4/3}^5(0.35), s_2^5(0.13), s_3^5(0.52)\right\}$	$\left\{s_3^5(0.66), s_{10/3}^5(0.30), s_4^5(0.04)\right\}$	$\left\{s_2^5(0.26), s_3^5(0.38), s_{10/3}^5(0.38), s_4^5(0.06)\right\}$	$\left\{s_{2/3}^5(0.06), s_2^5(0.53), s_3^5(0.42)\right\}$	$\left\{s_1^5(0.32), s_{4/3}^5(0.06), s_2^5(0.62)\right\}$
A_4	$\left\{s_0^5(0.42), s_1^5(0.23), s_2^5(0.35)\right\}$	$\left\{s_2^5(0.68), s_3^5(0.14), s_{8/3}^5(0.18)\right\}$	$\left\{s_1^5(0.22), s_2^5(0.72), s_3^5(0.06)\right\}$	$\left\{s_{4/3}^5(0.06), s_2^5(0.52), s_3^5(0.42)\right\}$	$\left\{s_2^5(0.02), s_3^5(0.74), s_{10/3}^5(0.24)\right\}$

Comparative analysis and discussion

In this section, to verify the rationality and feasibility of the multi-granularity extended probabilistic linguistic best—worst and VIKOR methods, we provide some comparative analysis with the existing MAGDM methods [32, 45]. The corresponding calculations and analysis are all based on the same scenario mentioned above. Tavana et al. [45] proposed an interval type-2 fuzzy best–worst method and combined compromise solution to evaluate eco-friendly packaging alternatives. They rank alternatives in descending order by calculating the final index value expressing the overall importance ξ_i of alternatives to determine the best one. Qin et al. [32] proposed the extended TODIM method in interval type-2 fuzzy environment for GSS. They rank alternatives by calculating the global prospect values π_i of alternatives to determine the best one. Table 7 shows the ranking results obtained by the three approaches, and it can be clearly seen that ranking order obtained by the methods in Qin et al. [32] and Tavana et al. [45] is slightly different from the ranking obtained by the proposed approach, but the best alternative is the same.

Compared with these methods, the features of the proposed model can be summarized in the following aspects. On the one hand, compared to Tavana et al.'s [45] research, our study can provide sets of compromise results, which the decision-makers can easily respond to various situations. However, the interval type-2 fuzzy best–worst method and combined compromise solution obtain a complete ranking order, and our ranking results are flexible. In addition, Tavana et al.'s [45] method gives decision-makers the same weight, while in real cases, decision-makers should be allocated with different weights according to their expertise. Our proposed multi-granularity extended probabilistic linguistic best–worst method enables the trade representatives to evaluate the expertise of decision-making panel by linguistic judgments, and we construct an optimization model to obtain the weights of decision-making panel. Furthermore, this optimization model is easy to understand and feasible, which makes the weight allocation to decision-making panels more scientific and reasonable. On the other hand, compared with Qin et al.'s [32] method, this study introduces the MGEPLTSs to the best–worst and VIKOR methods. The introduction of MGEPLTSs provides a flexible approach for decision-makers to give the evaluation information of alternatives, which can increase the reasonability of the final ranking results. Thus, they accord well with practice and can effectively handle uncertainty. However, in Qin et al.'s [32] method, the interval type-2 fuzzy sets are in the form of symmetrical triangular fuzzy numbers. This practice is improper to some extent. In addition, the TODIM method itself is vulnerable to two paradoxes affecting the weight of the model. For example, if one criteria weight approaches zero, the paradox appears. Also, the TODIM method is based on pairwise

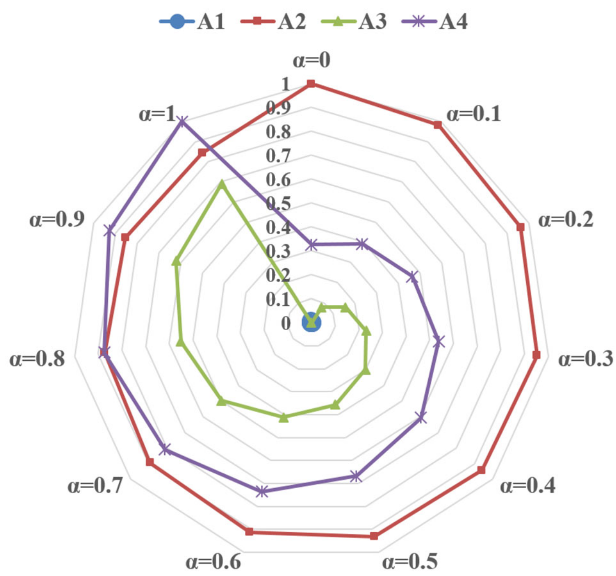

Fig. 2 The compromise measure under different values of α

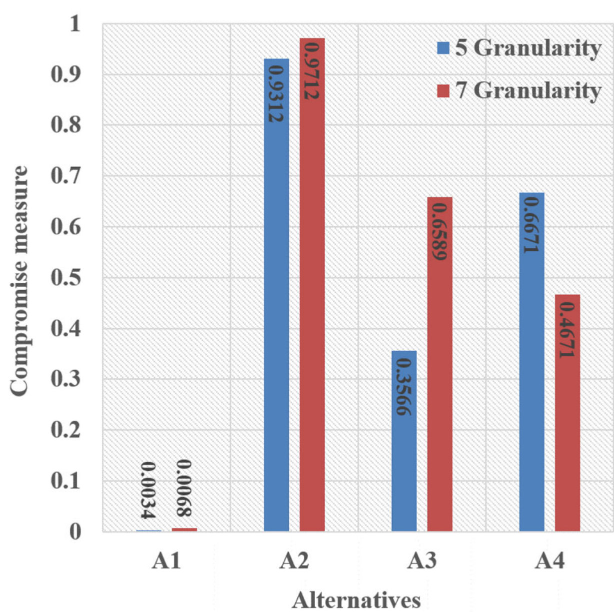

Fig. 3 The compromise measure of different alternatives under 5 and 7 granularities

comparisons and thus may suffer the rank-reversal phenomenon when some alternatives are added or deleted. Thus, much room for improvement remains. Therefore, through the comparative analysis, the proposed method can be applied in the process of the GSS in a more comprehensive perspective.

As shown in Figs. 2 and 3, by modifying the relevant parameters for sensitivity analysis, it can be seen that the changes of the parameters have slight effect on the final ranking results, which illustrates the robustness of this proposed approach. Furthermore, through the comparative analysis, it can reflect the reliability of the proposed approach. According to the above analysis, we can conclude that the proposed approach has the following advantages:

- The proposed approach uses the MGEPLTSs as the quantitative tool for decision-makers to make evaluation information. MGEPLTSs can well address the complexity and uncertainty problems, so it provides a flexible approach for decision-makers to give the evaluation information, which is not considered in Qin et al.'s [32] approach. Meanwhile, the three multi-granularity linguistic term sets are provided, which is helpful for the final qualified evaluation results to be closer to the real assessments of decision-makers.
- A new combined the multi-granularity extended probabilistic linguistic terms with BWM method is conducted. Specifically, the best–worst method and MGEPLTSs are fused, and then, the fuzzy mathematical programming model is constructed to solve the weights of decision-making panels and evaluation attributes, which make the model more suitable to deal with real cases. At the same time, the multi-granularity extended probabilistic linguistic best–worst method can consider the decision-making process and deal with the GSS problems more effectively, which is not considered in Qin et al. [32] and Tavana et al. [45].

The multi-granularity extended probabilistic linguistic VIKOR method is applied to rank alternatives, providing sets of compromise results and the decision-makers can easily respond to various situations, which is not considered in Tavana et al.'s [45] approach. Furthermore, sensitivity analysis regarding different parameters and different standard granularities is conducted to verify the final ranking results, which increase robustness of results and make the ranking results more accurate than previous interval type-2 fuzzy set-based TODIM method in Qin et al. [32], and interval type-2 fuzzy information-based MULTIMOORA method in Tavana et al. [45].

Additional discussion

We also experimented with other sets of values to investigate the sensitivities of these parameters on the computation results, with respect to the overall probabilistic linguistic decision-making matrix of decision-making panels. To achieve this intention, we have conducted the sensitivity analysis using different parameters and different standard granularities to examine their effects on the decision-making results based on two sets of experimental values. However, the detailed results are not presented here due to the space limitations but can be provided on request. It is similar to the

Table 7 The ranking results obtained by the three approaches

Methods	Literature	Ranking indices	Ranking results
Interval type-2 fuzzy best–worst method and combined compromise solution	Tavana et al. [45]	$\xi_i = (1.9812,\ 1.5501,\ 1.4267,\ 1.8225)$	$A_1 \succ A_4 \succ A_2 \succ A_3$
Extended TODIM method in interval type-2 fuzzy environment	Qin et al. [32]	$\pi_i = (1.0000,\ 0.4521,\ 0.7869,\ 0.0000)$	$A_1 \succ A_3 \succ A_2 \succ A_4$
Integrated BWM-VIKOR approach with MGEPLTSs	Our work	$\pi_i = (0.0034,\ 0.9312,\ 0.3566,\ 0.6671)$	$A_1 \succ A_3 \succ A_4 \succ A_2$

above experiments and sensitivity analysis in Section "Sensitivity analysis", the research results based on other sets of values using different parameters are also robust, namely the ranking of alternatives changes with the values of different parameter α, but the best alternative is always the same. Meanwhile, if any multi-granularity is selected as the standard granularity, the decision information before and after conversion is equivalent and has slight effect on the comprehensive dominance and ranking result.

Conclusions and future directions

With consideration for the resource depletion and environmental degradation being on the rise today, there are an increasing number of manufacturing plants which are willing to cooperate with green suppliers under the fierce marketing competition. Hence, selecting the appropriate green supplier is one of the utmost issues for GSCM practitioners to trade off the economic benefit and the environment friendliness. To achieve this intention, the methodology development, extension and application on the GSS problems are of essential significance. Although many fuzzy multi-attribute decision-making approaches have already been introduced and applied to handle GSS problems, those models cannot consider the bounded rationality behaviors of GSCM practitioners and cannot address group decision making problems in fuzzy environment and obtain compromise solutions as well. In this paper, we focus on the integrated MAGDM approach under MGEPLTSs environment for GSS practices by integrating the MGEPLTSs with the BWM and the classical linguistic decision VIKOR method.

To address the issues on potential ambiguity and uncertainty in actual GSCM practices, we extend a new MGEPLTSs to quantify the decision information of GSS problems in the inspiration of PLTSs, in which all the evaluation information and index weights information given by GSCM practitioners are represented by the MGEPLTSs. It can comprehensively and effectively reflect the real opinions of GSCM practitioners and maintain the integrity of original evaluation information as well. Besides, according to the results of sensitivity analysis and comparative analysis with other similar approaches, the MGEPLTS-based VIKOR method increases robustness of results and makes the ranking of alternatives more accurate than previous interval type-2 fuzzy set-based TODIM method in Qin et al. [32], and interval type-2 fuzzy information-based MULTIMOORA method in Tavana et al. [45]. Then, the BWM, as an effective multi-attribute decision-making method that constructs a comparison system in a structured manner and reduces inconsistency, is introduced to the MGEPLTSs environment to solve the weights of decision-making panels and evaluation attributes in GSS problems. This method requires fewer pairwise comparison than does fuzzy AHP and can obtain more reasonable weights than do BWM and fuzzy BWM. Finally, in combination with the well-known method called VIKOR, we extend a novel integrated MAGDM approach for GSS practices. Perhaps most importantly, the practical advantage of the developed method is that it defines a new research paradigm on the linguistic decision-making using MGEPLTSs rather than previous interval type-2 fuzzy sets. Meanwhile, it can provide an integration of various criteria on the basis of previous literature review, so we can have a clear and deep understanding on the critical success factors affecting GSCM practices, thereby promoting the flexibility and convenience of green supplier decision-making process. These criteria can be applied as the benchmarking and improvement tools that in this case can reconcile the proven aspects on the environmental practices.

An illustrative application on GSS is conducted, and the research results of sensitivity analysis and comparison analysis with other methods further validate the feasibility and reliability of our work in practice. The findings indicate the proposed approach can effectively address the complexity and uncertainty issues in GSS problems, which is useful for GSCM practitioners to select the optimal green supplier to implement GSCM practice and provides a new idea for the linguistic decision-making approach. In the future research, it will be worth studying to express the evaluation information of decision-makers in other ways, such as the generalized EPLTSs. Furthermore, it is also worth integrating the AHP, DEMATEL, PROMETHEE and so on with the

VIKOR method to compute the index weights. Finally, the proposed approach in this paper is applicable in many similar fields, such as the low carbon supplier selection, E-commerce service, strategic supplier selection, and hotel location selection.

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Author contributions CZ: Data curation, writing-original draft, writing review & editing; XW: Resources, investigation, methodology.

Data availability The data used in this paper will be available on request, please contact the corresponding author.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Alattas K, Wu Q (2022) A framework to evaluate the barriers for adopting the internet of medical things using the extended generalized TODIM method under the hesitant fuzzy environment. Appl Intell 52:13345–13363
2. Asadabadi MR, Ahmadi HB, Gupta H, Liou JJH (2022) Supplier selection to support environmental sustainability: the stratified BWM TOPSIS method. Ann Oper Res. https://doi.org/10.1007/s10479-022-04878-y
3. Awasthi A, Govindan K, Gold S (2018) Multi-tier sustainable global supplier selection using a fuzzy AHP-VIKOR based approach. Int J Prod Econ 195:106–117
4. Bakeshlou EA, Khamseh AA, Asl MAG, Sadeghi J, Abbaszadeh M (2017) Evaluating a green supplier selection problem using a hybrid MODM algorithm. J Intell Manuf 28:913–927
5. Bhuniya S, Pareek S, Sarkar B (2022) A sustainable game strategic supply chain model with multi-factor dependent demand and markup under revenue sharing contract. Complex Intell Syst. https://doi.org/10.1007/s40747-022-00874-8
6. Büyüközkan G, Tüfekçi G (2021) A decision-making framework for evaluating appropriate business blockchain platforms using multiple preference formats and VIKOR. Inf Sci 571:337–357
7. Celik E, Yucesan M, Gul M (2021) Green supplier selection for textile industry: a case study using BWM-TODIM integration under interval type-2 fuzzy sets. Environ Sci Pollut Res 28:64793–64817
8. Chen TY (2022) An evolved VIKOR method for multiple-criteria compromise ranking modeling under T-spherical fuzzy uncertainty. Adv Eng Inform 54:101802
9. Demir L, Akpınar ME, Araz C, Ilgın MA (2018) A green supplier evaluation system based on a new multi-criteria sorting method: VIKORSORT. Expert Syst Appl 114:479–487
10. Ding Q, Wang Y, Goh M (2021) TODIM dynamic emergency decision-making method based on hybrid weighted distance under probabilistic hesitant fuzzy information. Int J Fuzzy Syst 23:474–491
11. Du Y, Liu D (2021) An integrated method for multi-granular probabilistic linguistic multiple attribute decision-making with prospect theory. Comput Ind Eng 159:107500
12. Ecer F (2022) Multi-criteria decision making for green supplier selection using interval type-2 fuzzy AHP: a case study of a home appliance manufacturer. Oper Res Int J 22:199–233
13. Fei T, Peide L, Witold P (2021) A novel method based on probabilistic linguistic term sets and its application in ranking products through online ratings. Int J Intell Syst 36:4632–4658
14. Gao J, Xu ZS, Liang ZL, Liao HC (2019) Expected consistency-based emergency decision making with incomplete probabilistic linguistic preference relations. Knowl-Based Syst 176:15–28
15. Govindan K, Kadziński M, Sivakumar R (2017) Application of a novel PROMETHEE-based method for construction of a group compromise ranking to prioritization of green suppliers in food supply chain. Omega-Int J Manag Sci 71:129–145
16. He F, Miao X, Wong CWY, Lee S (2018) Contemporary corporate eco-innovation research: a systematic review. J Clean Prod 174:502–526
17. Kilic HS, Yalcin AS (2020) Modified two-phase fuzzy goal programming integrated with IF-TOPSIS for green supplier selection. Appl Soft Comput 93:106371
18. Kumar P, Singh RK, Paul J, Sinha O (2021) Analyzing challenges for sustainable supply chain of electric vehicle batteries using a hybrid approach of Delphi and best-worst method. Resour Conserv Recycl 175:105879
19. Lahri V, Shaw K, Ishizaka A (2021) Sustainable supply chain network design problem: using the integrated BWM, TOPSIS, possibilistic programming, and ε-constrained methods. Expert Syst Appl 168:114373
20. Li L, Shan S, Dai J, Che W, Shou Y (2022) The impact of green supply chain management on green innovation: A meta-analysis from the inter-organizational learning perspective. Int J Prod Econ 250:108622
21. Liang F, Brunelli M, Rezaei J (2022) Best-worst Tradeoff method. Inf Sci 610:957–976
22. Liang W, Goh M, Wang Y (2020) Multi-attribute group decision making method based on prospect theory under hesitant probabilistic fuzzy environment. Comput Ind Eng 149:106804
23. Liang Y, Tu Y, Ju Y, Shen W (2019) A multi-granularity proportional hesitant fuzzy linguistic TODIM method and its application to emergency decision making. Int J Disaster Risk Reduct 36:101081
24. Liao HC, Wen Z, Liu L (2019) Integrating BWM and ARAS under hesitant linguistic environment for digital supply chain finance supplier section. Technol Econ Dev Econ 25(6):1188–1212
25. Liou JJH, Chang MH, Lo HW, Hsu MH (2021) Application of an MCDM model with data mining techniques for green supplier evaluation and selection. Appl Soft Comput 109:107534
26. Liu PD, Zhu B, Wang P (2021) A weighting model based on best-worst method and its application for environmental performance evaluation. Appl Soft Comput 103:107168
27. Ma X, Qin J, Martínez L, Pedrycz W (2023) A linguistic information granulation model based on best-worst method in decision making problems. Inform Fusion 89:210–227

28. Masoomi B, Sahebi IG, Fathi M, Yıldırım F, Ghorbani S (2022) Strategic supplier selection for renewable energy supply chain under green capabilities (fuzzy BWM-WASPAS-COPRAS approach). Energ Strat Rev 40:100815
29. Mishra AR, Chen SM, Rani P (2022) Multiattribute decision making based on Fermatean hesitant fuzzy sets and modified VIKOR method. Inf Sci 607:1532–1549
30. Pang Q, Wang H, Xu Z (2016) Probabilistic linguistic term sets in multi-attribute group decision making. Inf Sci 369:128–143
31. Qi K, Chai H, Duan Q, Du Y, Wang Q, Sun J, Liew KM (2022) A collaborative emergency decision making approach based on BWM and TODIM under interval 2-tuple linguistic environment. Int J Mach Learn Cybern 13:383–405
32. Qin J, Liu X, Pedrycz W (2017) An extended TODIM multi-criteria group decision making method for green supplier selection in interval type-2 fuzzy environment. Eur J Oper Res 258:626–638
33. Qin J, Ma X (2022) An IT2FS-PT^3 based emergency response plan evaluation with MULTIMOORA method in group decision making. Appl Soft Comput 122:108812
34. Rezaei J (2016) Best-worst multi-criteria decision-making method: Some properties and a linear model. Omega-Int J Manag Sci 64:126–130
35. Rezaei J (2015) Best-worst multi-criteria decision-making method. Omega-Int J Manag Sci 53:49–57
36. Rostamzadeh R, Govindan K, Esmaeili A, Sabaghi M (2015) Application of fuzzy VIKOR for evaluation of green supply chain management practices. Ecol Ind 49:188–203
37. Samad S, Nilashi M, Almulihi A, Alrizq M, Alghamdi A, Mohd S, Ahmadi H, Azhar SNFS (2021) Green Supply Chain Management practices and impact on firm performance: the moderating effect of collaborative capability. Technol Soc 67:101766
38. Salimi N (2017) Quality assessment of scientific outputs using the BWM. Scientometrics 112:195–213
39. Sarkar B, Ganguly B, Pareek S, Ca'rdenas-Barro'n LE (2022) A three-echelon green supply chain management for biodegradable products with three transportation modes. Comput Ind Eng 174:108727
40. Samad S, Nilashi M, Almulihi A et al (2021) Green Supply Chain Management practices and impact on firm performance: the moderating effect of collaborative capability. Technol Soc 67:101766
41. Stojanovic V, Nedic N (2016) Joint state and parameter robust estimation of stochastic nonlinear systems. Int J Robust Nonlinear Control 26:3058–3074
42. Takalo SK, Tooranloo HS, Parizi ZS (2021) Green innovation: a systematic literature review. J Clean Prod 279:122474
43. Tao H, Cheng L, Qiu J, Stojanovic V (2022) Few shot cross equipment fault diagnosis method based on parameter optimization and feature metric. Meas Sci Technol 33:115005
44. Tavana M, Mina H, Santos-Arteaga FJ (2023) A general Best-Worst method considering interdependency with application to innovation and technology assessment at NASA. J Bus Res 154:113272
45. Tavana M, Shaabani A, Di Caprio D, Bonyani A (2022) A novel Interval Type-2 Fuzzy best-worst method and combined compromise solution for evaluating eco-friendly packaging alternatives. Expert Syst Appl 200:117188
46. Tian X, Li W, Liu L, Kou G (2021) Development of TODIM with different types of fuzzy sets: a state-of the-art survey. Appl Soft Comput 111:107661
47. Tian ZP, Wang JQ, Wang J, Zhang HY (2018) A multi-phase QFD-based hybrid fuzzy MCDM approach for performance evaluation: a case of smart bike-sharing programs in Changsha. J Clean Prod 171:1068–1083
48. Verdecho MJ, Alarcón-Valero F, Pérez-Perales D, Alfaro-Saiz JJ, Rodríguez-Rodríguez R (2021) A methodology to select suppliers to increase sustainability within supply chains. CEJOR 29:1231–1251
49. Wan S, Huang Cheng W, Dong J (2021) Interactive multi-criteria group decision-making with probabilistic linguistic information for emergency assistance of COVID-19. Appl Soft Comput 107:107383
50. Wang F, Lai X, Shi N (2011) A multi-objective optimization for green supply chain network design. Decis Support Syst 51:262–269
51. Wang L, Zhang Z, Wang Y (2015) A prospect theory-based interval dynamic reference point method for emergency decision making. Expert Syst Appl 42:9379–9388
52. Wang Z, Fung RYK, Li Y, Pu Y (2016) A group multi-granularity linguistic-based methodology for prioritizing engineering characteristics under uncertainties. Comput Ind Eng 91:178–187
53. Wu Q, Zhou L, Chen Y, Chen H (2019) An integrated approach to green supplier selection based on the interval type-2 fuzzy best-worst and extended VIKOR methods. Inf Sci 502:394–417
54. Wu X, Liao HC (2022) Geometric linguistic scale and its application in multi-attribute decision-making for green agricultural product supplier selection. Fuzzy Sets Syst. https://doi.org/10.1016/j.fss.2022.08.026
55. Wu X, Liao HC, Xu ZS, Hafezalkotob A, Herrera F (2018) Probabilistic linguistic MULTIMOORA: a multicriteria decision Making method based on the probabilistic pinguistic expectation function and the improved Borda rule. IEEE Trans Fuzzy Syst 26:3688–3702
56. Yazdani M, Chatterjee P, Zavadskas EK, Zolfani SH (2016) Integrated QFD-MCDM framework for green supplier selection. J Clean Prod 142:3728–3740
57. Yazdi M, Nedjati A, Zarei E, Abbassi R (2020) A reliable risk analysis approach using an extension of best-worst method based on democratic-autocratic decision-making style. J Clean Prod 256:120418
58. Zhang L, Liang C, Li T, Yang W (2022) A two-stage EDM method based on KU-CBR with the incomplete linguistic intuitionistic fuzzy preference relations. Comput Ind Eng 172:108552
59. Zhang Q, Wang Y, Cheng J, Yan H, Shi K (2023) Improved filtering of interval type-2 fuzzy systems over Gilbert-Elliott channels. Inf Sci 627:132–146
60. Zhang Y, Xu Z, Liao H (2017) A consensus process for group decision making with probabilistic linguistic preference relations. Inf Sci 414:260–275
61. Zhang Y, Zhao H, Li B, Zhao Y, Qi Z (2022) Research on credit rating and risk measurement of electricity retailers based on Bayesian Best Worst Method-Cloud Model and improved Credit Metrics model in China's power market. Energy 252:124088
62. Zhang Z, Song X, Sun X, Stojanovic V (2023) Hybrid-driven-based fuzzy secure filtering for nonlinear parabolic partial differential equation systems with cyber attacks. Int J Adapt Control Signal Process 37(2):380–398