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Multi-criteria group decision-making method for green supplier selection based on distributed interval variables

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ABSTRACT

Addressing the multi-criteria group decision making problem with interval attribute values and attribute weights, this paper proposes a decision method based on attribute distribution information. The selection of green suppliers is taken as an example for decision analysis. First, in the case of group decision-making, the quantitative values of the evaluation attributes of green suppliers are imputed by decision-makers, and the relevant distributions are constructed for each attribute. Next, combined with the ranges of attribute values, the random interval values are used to describe the information represented by each attribute to overcome the loss caused by the aggregation of individual expert information into group information. We then propose the distributed interval weighted arithmetic average (DIWAA) operator and corresponding operation rules, which realizes the fusion of qualitative data and quantitative judgment. Thus, the proposed approach allows ensuring reasonable results of the multi-criteria analysis. We also construct a ranking method for alternatives based on distributed interval comprehensive scores. Finally, we verify the feasibility and effectiveness of the proposed method for the task of green supplier selection through numerical experiments.

1. Introduction

Proper supply chain management has appeared as a crucial element of corporate performance (Jin & Wang, 2020; Kot et al., 2020). The significant increase in scarcity of resources has pushed many countries to devote increased attention toward green production behavior (Pan et al., 2020; Rane & Thakker, 2019) and emphasize coordinated relationships between economy and sustainable development (Kiseláková et al., 2019). This is expected to improve the environment and ensure the proper material flows (Ma et al., 2019). In the recent years, more and more companies are assigning high importance to green supply chain management to reduce their own production

costs and the negative effects of production activities. Indeed, changes in the external environment may impact the corporate behavior (Du et al., 2020).

The Michigan State University Manufacturing Research Association first proposed the concept of green supply chains (Shan & Wang, 2018). Compared to traditional supply chains, green supply chains are comprehensively integrated with the concept of 'green production' and fully focus on the impact of production operations and environmental standards. Such supply chains require enterprises to adopt green manufacturing theory and apply supply chain management technology to maximize the efficiency of resource outputs and minimize negative impacts on the environment in the process of product processing, packaging, storage, transportation, use, and scrap disposal.

Based on the upstream position of suppliers in a supply chain, the quality of the raw materials, semi-finished products, or services they provide not only directly affects the quality of the final products of downstream companies, but it also determines the potential for environmental protection and production efficiency. However, considering environmental impact, selecting a suitable green supplier can be difficult based on the following two aspects. First, the characteristics for judging green suppliers are vague and subjective, and the asymmetry of information yields imperfect decision-making attributes. Second, when choosing a supplier, a decision-maker must consider both their own economic benefits and external environmental factors, which increases the complexity of decision-making. Based on these factors, scholars have devoted significant attention to the selection of green suppliers.

For the choice of green suppliers, due to the fuzziness of things and the subjectivity of decision makers, decision makers cannot use accurate data to describe qualitative data, nor can they give accurate decision information. To solve this problem, this paper mainly improves the decision method in the following aspects. One is to incorporate the concept of modular computing into the decision making process by considering the differences in the distribution characteristics between attribute values when both attributes and weights are distributed. Second, instead of assuming the distribution of supplier's decision attributes, the frequency distribution is used for calculation and the cumulative distribution is used for comparison. Three is to make decisions by using the relative advantages of ranking rules and comprehensive decision values of cumulative distribution areas, so as to make the decision results more reasonable.

This paper is organized as follows. Section 3 presents preliminary knowledge regarding attribute distributions and distributed interval variables. The integrated operator for attribute information and its operation rules are introduced in Sec. 4. In Secs. 5 and 6, the proposed decision-making method based on distributed interval variables is summarized. An illustrative example of green supplier selection is presented in Sec. 7.

2. Literature review

In the existing literature, a few scholars focused on adding green constraints to green supplier selection criteria and adopted analytic hierarchy process (AHP), data

envelopment analysis (DEA), and operational optimization to make decisions. Handfield et al. (2002) took AHP as a decision support model to assess the relative importance of various environmental characteristics to supplier selection. Noci (1997) applied AHP to supplier environmental performance evaluation. In different application scenarios, it is a common research practice to construct decision criteria for green suppliers and use AHP to make decisions (Chiou et al., 2008; Liao et al.,2015; Lu et al., 2007; Yu & Hou, 2016). Other studies have applied DEA to solve the selection of potential green suppliers (Banaeian et al., 2014; Dobos & Vorosmarty, 2019). Khalilzadeh and Derikvand (2018) and Papen and Amin (2019) proposed a stochastic programming model and multi-objective programming model, respectively, to solve the problem of supplier selection in green supply chains. Abdullah et al. (2019) applied the preference ranking organization method for enrichment evaluation (PROMETHEE) to the selection of green suppliers. Yazdani et al. (2016) and Liao et al. (2020) both proposed the Stepwise Weight Assessment Ratio Analysis (SWARA) method for supplier selection in fuzzy linguistic environment. The abovementioned methods mainly describe related decision attributes in the form of precise values. However, when making selection decisions for green suppliers, it is often necessary to adopt an attribute system combining qualitative and quantitative data. If decision-makers describe qualitative data using precise values, it could lead to greater ambiguity and uncertainty. Therefore, to consider quantitative data defects in the form of point values, some scholars have proposed methods to describe and process attribute data and decision criteria using the theory of fuzzy sets (Banaeian et al., 2018; Boran et al., 2009; Gao et al., 2017; Gitinavard et al., 2018; Hsu et al., 2007; Tian et al., 2018; Ulutaş et al., 2019). On the basis of fuzzy sets, some scholars have designed methods for selecting green suppliers in combination with other variables with fuzzy characteristics, such as grey values (Haeri and Rezaei, 2019; Quan et al., 2018; Sun et al., 2018; Vishnu et al., 2018), intuitionistic fuzzy sets (Yin et al., 2017), Pythagorean fuzzy sets (Yu et al., 2019; Zhang et al., 2021).

Similarly, some studies have used interval-valued variables to describe the ambiguity of data and used it to perform group decision-making for the selection of green suppliers (Liang et al., 2019; Mohammadi et al., 2017; Mousakhani et al., 2017; Wu et al., 2019; Xu et al., 2018). Other studies have discussed decision-making methods for supplier selection in the context of linguistic variables. For example, based on single-valued neutrosophic linguistic data combined with the TOPSIS method, Chen et al. (2018) designed a supplier selection method for low-carbon supply chains. Wang et al. (2020) proposed single-valued neutrosophic linguistic logarithmic weighted distance measures and applied them to supplier selection for fresh aquatic products.

Probabilistic decision information has been addressed and proposals for a series of decision-making methods based on probabilistic linguistic term set (PLTS) have been made. For example, Luo et al. (2020) considered the decision-making environment of PLTS and proposed a novel correlation coefficient that was applied to the evaluation of hospital suppliers. Wen et al. (2019) proposed a model combining stepwise weight assessment ratio analysis (SWARA) and the combined compromise solution (CoCoSo) method for probabilistic linguistic decision-making environments and applied it to the selection of drug suppliers.

As discussed above, the use of fuzzy set theory or interval variables to describe attribute information can partially solve the issue of information ambiguity and incompleteness in green supplier selection problems. However, for the application of decision-making, most previous studies have adopted the processing method of converting related attribute data into real numbers. However, such processing will lead to a loss of attribute information. From a dynamic perspective, to select a suitable supplier, a decision-maker must consider the historical performance of alternative suppliers and refer to the satisfaction of other users with those suppliers. In such scenarios, we must investigate and collect relevant information. Attribute information has certain distribution characteristics. However, existing decision-making methods tend to simplify attribute distribution information, such as assuming that it follows a uniform distribution and calculating average values. Such processing leads to a loss of decision information. Although the PTLS considers the probabilities of decision-maker's judgments, linguistic values are typically set to a finite set of possible values, which limits the effective acquisition of attribute distribution information.

To describe a supplier's operational performance or service status, regardless of whether it is historical performance or service satisfaction, this information can be collected through multiple continuous surveys (multiple surveys conducted simultaneously or under dynamic conditions).For dynamic information from multiple surveys, to utilize distributed interval variables to describe attribute information, we propose a decision-making method based on attribute distribution information combined with the proposed distributed interval weighted arithmetic average (DIWAA) operator. The proposed method is then applied to decision-making for green supplier selection. To facilitate explanation of the problem, we focus on the usefulness of the proposed method for group decision-making.

3. Preliminaries

3.1. Attribute distributions in group decision-making

For a group decision-making problem with a finite number of alternatives, consider a set of alternatives $P = \{p_1, p_2, \ldots, p_t\}$. Further, let $G = \{g_1, g_2, \ldots g_m\}$ be the set of decision-makers, and $A = \{a_1, a_2, \ldots, a_n\}$ be the set of attributes. A certain decision maker g_i assigns the attribute value of the alternative p_k $(1 \leq k \leq t)$ for attribute $a_j(1 \leq j \leq n)$ via scoring and adopts a single-round decision-making process without feedback. The decision-making matrix for the alternative p_k is as follows:

$$E^k = \left[e_{ij}^k\right]_{m \times n} = \begin{bmatrix} e_{11}^k & e_{12}^k & \cdots & e_{1n}^k \\ e_{21}^k & e_{22}^k & \cdots & e_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ e_{m1}^k & e_{m2}^k & \cdots & e_{mn}^k \end{bmatrix}.$$

Different values in the sequence $\left\{e_{ij}^k\right\}(1 \leq i \leq m)$ indicate that decision makers have inconsistent views regarding the quantification of attribute a_j. According to the sequence $\left\{e_{ij}^k\right\}$, we can capture the distribution characteristics of a certain attribute

value. When integrating the information from multiple decision-makers, considering such distribution features helps to ensure the consistency of decision maker views.

Definition 1. We arrange the sequence $\left\{e_{ij}^k\right\}(1 \leq i \leq m)$ in ascending order and merge duplicate elements, resulting in a sequence $x_j^k = \left\{x_{j1}^k, x_{j2}^k, \ldots, x_{jq}^k\right\}(q \leq m)$, which is called the ordered sequence of attribute a_j^k.

Definition 2. According to sequence x_j^k, the decision-maker set $G = \{g_1, g_2, \ldots, g_m\}$ can be divided into q categories (levels). Then, there is a subgroup set $B_j^k = \left\{B_{j1}^k, B_{j2}^k, \ldots, B_{jq}^k\right\}$, where $B_{ji}^k(1 \leq i \leq q)$ is the subgroup of decision makers for attribute a_j^k choosing x_{ji}^k.

Definition 3. Assuming that b_{ji}^k is the number of decision makers in subgroup B, the subgroup frequency can be calculated as

$$f_{ji}^k = \frac{b_{ji}^k}{m}. \tag{1}$$

Then, sequence $f_j^k = \left\{f_{j1}^k, f_{j2}^k, \ldots, f_{jq}^k\right\}$ is called the group frequency sequence of B_j^k.

Definition 4. For a sequence x_j^k, the distribution of alternative p_k for attribute a_j^k can described via the density function

$$f\left(x_j^k\right) = \begin{cases} f_{ji}^k & x_j^k = x_{ji}^k(1 \leq i \leq q) \\ 0 & \text{otherwise} \end{cases}. \tag{2}$$

Here, we have $\sum_{i=1}^q f_{ji}^k = 1$.

The value distribution for a given attribute is not exactly the same between different alternatives, which fully reflects the particularity of alternatives. Although attribute distributions describe all possible values, they can also reflect the distribution characteristics of a group's quantitative differences and represent the characteristics of outlier data, which is helpful for handling such data appropriately.

3.2. Distributed interval variable

The distribution characteristics of attribute values represent the uncertainty of attribute quantification for each member in a set of decision makers. Therefore, attribute values can be regarded as random variables that fall within a certain range. Some scholars simply assume that the distributions of attributes are uniform or normal. However, there is an ongoing debate regarding whether this assumption is too idealistic. In the proposed method, we describe the attribute values for group decision-making using distributed interval variables without assuming distribution characteristics in advance, which will be discussed below.

Definition 5. Let $\tilde{x} = [z^l, z^u] = \left\{ x : z^l \leq x \leq z^u, x \in I(R) \right\}$ be an interval variable, where z^l and z^u represent the lower bound and upper bound of the interval variable, respectively, and $I(R)$ represents the set of all bounded closed intervals.

Definition 6. Assuming that x is a random variable and the density function within the interval $[z^l, z^u]$ is $\varphi(x)$, the corresponding distributed interval variable can be described as $z = \left\{ [z^l, z^u], \varphi(x) \right\}$.

Consider alternative p_k as an example. By using Definition 6, we can obtain the random interval value $z_j^k = \left\{ \left[z_j^{kl}, z_j^{ku} \right], f(x_j^k) \right\}$ of the decision-maker set for attribute a_j, where we have $z_j^{kl} = \min_{1 \leq i \leq m}(e_{ij}^k)$ and $z_j^{ku} = \max_{1 \leq i \leq m}(e_{ij}^k)$. In the same manner, we can also obtain the random interval weight of attribute a_j, which can be expressed as $\omega_j^k = \left\{ \left[\omega_j^{kl}, \omega_j^{ku} \right], f(y_j^k) \right\}$.

4. Integrated operator for random interval values

4.1. DIWAA operator

The process of information aggregation in group decision-making involves two sub-processes: individual information aggregation and attribute information aggregation. As distribution information reflects a group's judgment regarding attribute values or weights and maintains the evaluation information for each individual, the construction of a distributed interval value can be regarded as the process of aggregation of individual information. Aggregating attribute information effectively is the main problem to be solved for group decision-making problems. Further, we describe the proposed DIWAA operator in details. The corresponding operational rules will be introduced later in the paper.

Definition 7. Assume that the attribute dataset is $A = \{a_1, a_2, \ldots, a_n\}$, where $a_i = \left[(a_i^l, a_i^u), f(a) \right]$ and $DIWAA : R^n \to R$ is the DIWA aggregation operator, if

$$DIWAA_\omega(a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} \omega_i a_i, \tag{3}$$

where $\omega_i = \left[(\omega_i^l, \omega_i^u), f(\omega) \right]$ represents the weight of attribute i and meets the requirements of normalization.

4.2. Operational rules

The DIWAA operator mainly involves the addition and multiplication of random interval values. For convenience of description, it is assumed that a random interval attribute value and corresponding random interval attribute weight are expressed as $z_1 = \left[(z_1^l, z_1^u), f(x) \right]$ and $z_2 = \left[(z_2^l, z_2^u), g(y) \right]$, respectively, where density functions $f(x)$ and $g(y)$ represent the distribution of z_1 and z_2, respectively. These functions are expressed as follows:

$$f(x) = \begin{cases} f(x_i) & x = x_i (i = 1, 2, \ldots, r) \\ 0 & otherwise \end{cases}, \tag{4}$$

$$g(y) = \begin{cases} g(y_j) & y = y_j (j = 1, 2, \ldots, s) \\ 0 & otherwise \end{cases}. \tag{5}$$

Definition 8. For random interval values z_1 and z_2, $T^*[T_{ij}]_{r \times s}$ and $V^*[V_{ij}]_{r \times s}$ are called the possible value matrix and joint probability matrix of $z = z_1 \odot z_2$, respectively, where $T_{ij} = x_i \odot y_j$ and $V_{ij} = f(x_i)g(y_j)$ $(1 \le i \le r; 1 \le j \le s)$. Note that $\odot = \{\oplus, \otimes\}$.

For instance, if $\odot$ represents an addition operation $\oplus$, then we have $T_{ij} = x_i + y_j$, and T^* is the possible sum matrix of $z = z_1 \oplus z_2$. When $\odot$ represents a multiplication operation, we have $T_{ij} = x_i y_j$, and T^* is the possible sum matrix of $z = z_1 \otimes z_2$.

Definition 9. In matrices T^* and V^*, two elements T_{ij} and V_{ij} that are in the same row i and column j are called corresponding element groups and denoted as $Q_{ij} = \langle T_{ij}, V_{ij} \rangle$.

Definition 10. According to the value of T_{ij}, all elements in matrix T^* are grouped to construct an ordered sequence $T = \{\bar{T}_1, \bar{T}_2, \ldots, \bar{T}_q\}$ $(1 \le q \le rs)$, which is called the ordered sequence of possible values of $z = z_1 \odot z_2$.

Similar to Definition 8, if $\odot$ is an addition operation, then T is called an ordered possible sum sequence, and if $\odot$ is a multiplication operation, then it is called an ordered possible product sequence.

Definition 11. Using the ordered sequence of possible values T, the ordered corresponding element group $\bar{Q}_r = \langle \bar{T}_r, \bar{V}_r \rangle$ $(1 \le r \le q)$ can be constructed, where $\bar{V}_r$ represents the sum of all joint probabilities V_{ij} corresponding to all possible values T_{ij} that satisfies the condition $T_{ij} = \bar{T}_d$ $(1 \le d \le q)$ in matrix T^*.

Definition 12. For two random interval values z_1 and z_2, their addition and multiplication results can be uniformly expressed as $z = \{[\bar{T}_1, \bar{T}_q], \varphi(x)\}$, where

$$\varphi(x) = \begin{cases} \bar{V}_d & x = \bar{T}_d (1 \le d \le q) \\ 0 & otherwise \end{cases}. \tag{6}$$

When using addition operations, we have $\bar{T}_1 = \min_{i,j}(x_i + y_j)$ and $\bar{T}_q = \max_{i,j}(x_i + y_j)$. When using multiplication operations, we have $\bar{T}_1 = \min_{i,j}(x_i y_j)$ and $\bar{T}_q = \max_{i,j}(x_i y_j)$.

5. Decision-making method based on the DIWAA operator

According to the aforementioned definitions, addition and multiplication operations between multiple distributed interval values can be performed. Therefore, by using the DIWAA operator from Definition 7, a comprehensive score for each alternative

can be calculated. However, when making decisions, we cannot directly use the probability distributions of interval variables for ranking comparisons. Here, we present a ranking method based on the cumulative distributed interval values (CDIV).

5.1. Centroid of the CDIV

Definition 13. The comprehensive score of an alternative expressed in the form of a CDIV can be described as $Z = \{[T_1, T_q], F(x)\}$, where

$$
F(x) = \begin{cases} 0 & x < \bar{T}_1 \\ \sum_{i=1}^{k} \bar{V}_i & \bar{T}_k \le x < \bar{T}_{k+1} \\ 1 & x \ge \bar{T}_q \end{cases}.
\tag{7}
$$

Definition 14. Let $c = (\hat{x}, \hat{y})$ be the centroid of the comprehensive score of the cumulative distribution interval of an alternative, where $\hat{x}$ and $\hat{y}$ represent the first coordinate and second coordinate, respectively.

$$
\hat{x} = \frac{\sum_{i=1}^{q-1} \tilde{V}_i \left(\bar{T}_{i+1}^2 - \bar{T}_i^2\right)}{2 \sum_{i=1}^{q-1} \tilde{V}_i \left(\bar{T}_{i+1} - \bar{T}_i\right)},
\tag{8}
$$

$$
\hat{y} = \frac{\sum_{i=1}^{q-1} \tilde{V}_i^2 \left(\bar{T}_{i+1} - \bar{T}_i\right)}{2 \sum_{i=1}^{q-1} \tilde{V}_i \left(\bar{T}_{i+1} - \bar{T}_i\right)}.
\tag{9}
$$

This clearly represents the average position of the variable value weighted by the distribution probability, where $\hat{x}$ represents the total dispersion degree of the distribution probability. To eliminate differences in measurement scales, it is necessary to normalize the centroid of each alternative. Assuming that the center of the comprehensive score of the *ith* alternative is denoted as $c_i = (\hat{x}_i, \hat{y}_i)$ $(1 \le i \le t)$, the normalized values $zc_i = (z\hat{x}_i, z\hat{y}_i)$ are obtained as

$$
z\hat{x}_i = \frac{\hat{x}_i - \bar{x}}{\sqrt{\frac{1}{t-1} \sum_{i=1}^{t} (\hat{x}_i - \bar{x})^2}},
\tag{10}
$$

$$
z\hat{y}_i = \frac{\hat{y}_i - \bar{y}}{\sqrt{\frac{1}{t-1} \sum_{i=1}^{t} (\hat{y}_i - \bar{y})^2}}.
\tag{11}
$$

In Eqs. (10) and (11), we have $\bar{x} = \frac{\sum_{i=1}^{t} \hat{x}_i}{t}$ and $\bar{y} = \frac{\sum_{i=1}^{t} \hat{y}_i}{t}$.

5.2. Rules for ranking

By comparing the coordinate positions of centroids, alternatives can be ranked. It is worth noting that if two alternatives have the same first coordinate, then their second coordinates must be compared. The details of these rules are provided in Definition 15.

Definition 15. Suppose that the comprehensive scores of two alternatives are z_i and z_j. Then, their normalized centroids can be denoted as $zc_i = (z\hat{x}_i, z\hat{y}_i)$ and $zc_j = (z\hat{x}_j, z\hat{y}_j)$, respectively. The ranking rules can then be defined as follows:

(i) If $z\hat{x}_i > \hat{z}x_j$, then z_i is greater than z_j, which can be denoted as $z_i \succ_s z_j$.

(ii) If $z\hat{x}_i = z\hat{x}_j$, and the second coordinate between two alternatives has the following relationship, we can derive the corresponding conclusions.

(ii.1) If $z\tilde{y}_i > z\tilde{y}_j$, then z_i is smaller than z_j, which can be denoted as $z_i \prec z_j$.

(ii.2) If $z\hat{y}_i = z\hat{y}_j$, then z_i equal to z_j, which can be denoted as $z_i \sim z_j$.

(ii.3) If $z\hat{y}_i < z\hat{y}_j$, then z_i is greater than z_j, which can be denoted as $z_i \succ z_j$.

(iii) If $z\tilde{x}_i < z\tilde{x}_j$, then z_i is less than z_j, which can be denoted as $z_i \prec_s z_j$. It is worth noting that when there is a large number of alternatives, we must adopt a pair-wise comparison method to obtain an ordinal relationship between alternatives. To distinguish the different scenarios outlined above effectively, the ranking rules should be further quantified. In Definition 16, we assign corresponding values to different scenarios when comparing the centroids of alternatives.

Definition 16. Using a pair-wise comparison method, an ordinal relationship matrix $\tilde{\omega} = [\tilde{\omega}_{ij}]_{t \times t}$ between alternatives can be obtained, where the assignment rule for $\tilde{\omega}_{ij}$ is

$$\tilde{\omega}_{ij} = \begin{cases} 2 & z\hat{x}_i > z\hat{x}_j \\ 1 & z\hat{x}_i = z\hat{x}_j, z\hat{y}_i < z\hat{y}_j \\ 0 & z\hat{x}_i = z\hat{x}_j, z\hat{y}_i = z\hat{y}_j \\ -1 & z\hat{x}_i = z\hat{x}_j, z\hat{y}_i > z\hat{y}_j \\ -2 & z\hat{x}_i < z\hat{x}_j \end{cases} \tag{12}$$

It should be noted that in Eq. (12), the assignment of $\tilde{\omega}_{ij}$ does not distinguish the strengths of the 'greater than' or 'less than' relationships between alternatives. One effective solution is to compare the distances between alternatives comprehensively based on the ordering relationship. Therefore, Definition 17 is proposed.

Definition 17. The ordinal distance between two alternatives i and j can be expressed as

$$L\tilde{\omega}_{ij} = \tilde{\omega}_{ij} \times d_{ij}. \tag{13}$$

where $d_{ij} = \sqrt{(z\hat{x}_i - z\hat{x}_j)^2 + (z\hat{y}_i - z\hat{y}_j)^2}$ and $L = [L_{ij}]_{t \times t}$ is the ordinal distance matrix of the set of alternatives.

To obtain the ranking of all alternatives, Definition 18 is used to calculate the relative dominance of each alternative compared to the other alternatives.

Definition 18. When the number of alternatives is t, using the ordinal distance matrix L, the relative dominance of the ith alternative can be defined as $\bar{L}_i = \sum_{j=1}^{K} L_{ij}$.

6. Algorithm for MCDM based on the DIWAA operator

The steps of the proposed method are detailed below.

Step 1. After data are collected, according to Definitions 1 to 6, the interval of each attribute and its corresponding distribution function can be obtained, allowing us to construct distributed interval attribute values. Similarly, distributed interval attribute weights can also be obtained.

Step 2. Use the operation rules of the DIWAA operator to calculate the distributed interval value of each alternative according to Definitions 8 to 12.

Step 3. Transform the distributed interval comprehensive score into the cumulative distributed interval comprehensive score using Eq. (7).

Step 4. Calculate the normalized centroid of the cumulative distributed interval comprehensive score for each alternative.

Step 5. Compute the ordinal distance matrix of the set of alternatives using Definitions 16 and 17.

Step 6. Calculate the relative dominance of each alternative and rank the alternatives.

7. An illustrative example

To select suitable green suppliers, manufacturers invite a group of experts to evaluate three potential suppliers $P = [P_1, P_2, P_3]$ according to a criteria system including product performance (A_1), supplier development potential (A_2), cooperation ability (A_3), and environmental management ability (A_4). All attributes are quantified by experts and the experts are required to assign attribute weights within the value range of $[0, 1]$. After completing data collection and sorting, the organizer obtains the distributed interval attribute value of each alternative and distributed interval weight of each attribute. The relevant data are provided in Table 1.

In Table 1, the distributions of the attribute values and the attribute weights of each alternative can be described as follows:

$$f(x_1^1) = \begin{cases} 0.25 & x_1^1 = 7.4 \\ 0.4 & x_1^1 = 8.1, \\ 0.35 & x_1^1 = 8.7 \end{cases} f(x_2^1) = \begin{cases} 0.35 & x_2^1 = 7.2 \\ 0.2 & x_2^1 = 7.6 \\ 0.25 & x_2^1 = 8.6 \\ 0.2 & x_2^1 = 9.0 \end{cases}, f(x_3^1) = \begin{cases} 0.25 & x_3^1 = 7.3 \\ 0.25 & x_3^1 = 8.1 \\ 0.3 & x_3^1 = 8.7 \\ 0.2 & x_3^1 = 8.9 \end{cases},$$

$$f(x_4^1) = \begin{cases} 0.25 & x_4^1 = 7.6 \\ 0.4 & x_4^1 = 8.0 \\ 0.25 & x_4^1 = 8.4 \\ 0.1 & x_4^1 = 8.9 \end{cases}, f(x_1^2) = \begin{cases} 0.2 & x_1^2 = 7.0 \\ 0.35 & x_1^2 = 8.0 \\ 0.3 & x_1^2 = 8.6 \\ 0.15 & x_1^2 = 9.0 \end{cases}, f(x_2^2) = \begin{cases} 0.4 & x_2^2 = 7.1 \\ 0.25 & x_2^2 = 8.0, \\ 0.35 & x_2^2 = 8.8 \end{cases}$$

Table 1. Decision-making matrix for green supplier selection.

Alternative	Attribute weight	Attribute value		
		P_1	P_2	P_3
A_1	$\omega_1 = \{[0.1, 0.2], g(\omega_1)\}$	$z_1^1 = \{[7.4, 8.7], f(x_1^1)\}$	$z_1^2 = \{[7.0, 9.0], f(x_1^2)\}$	$z_1^3 = \{[7.2, 8.8], f(x_1^3)\}$
A_2	$\omega_2 = \{[0.15, 0.25], g(\omega_2)\}$	$z_2^1 = \{[7.2, 9.0], f(x_2^1)\}$	$z_2^2 = \{[7.1, 8.8], f(x_2^2)\}$	$z_2^3 = \{[7.0, 8.9], f(x_2^3)\}$
A_3	$\omega_3 = \{[0.2, 0.3], g(\omega_3)\}$	$z_3^1 = \{[7.3, 8.9], f(x_3^1)\}$	$z_3^2 = \{[7.2, 8.9], f(x_3^2)\}$	$z_3^3 = \{[7.3, 9.0], f(x_3^3)\}$
A_4	$\omega_4 = \{[0.1, 0.15], g(\omega_4)\}$	$z_4^1 = \{[7.6, 8.9], f(x_4^1)\}$	$z_4^2 = \{[7.5, 9.0], f(x_4^2)\}$	$z_4^3 = \{[7.1, 9.0], f(x_4^3)\}$

$$f(x_3^2) = \begin{cases} 0.2 & x_3^2 = 7.2 \\ 0.2 & x_3^2 = 7.8 \\ 0.3 & x_3^2 = 8.2 \\ 0.3 & x_3^2 = 8.9 \end{cases}, f(x_4^2) = \begin{cases} 0.25 & x_4^2 = 7.5 \\ 0.35 & x_4^2 = 8.2 \\ 0.25 & x_4^2 = 8.8 \\ 0.15 & x_4^2 = 9.0 \end{cases},$$

$$f(x_1^3) = \begin{cases} 0.2 & x_1^3 = 7.2 \\ 0.3 & x_1^3 = 7.6 \\ 0.3 & x_1^3 = 8.1 \\ 0.2 & x_1^3 = 8.8 \end{cases}, f(x_2^3) = \begin{cases} 0.3 & x_2^3 = 7.0 \\ 0.3 & x_2^3 = 8.0 \\ 0.4 & x_2^3 = 8.9 \end{cases},$$

$$f(x_3^3) = \begin{cases} 0.2 & x_3^3 = 7.3 \\ 0.25 & x_3^3 = 7.9 \\ 0.3 & x_3^3 = 8.1 \\ 0.25 & x_3^3 = 9.0 \end{cases}, f(x_4^3) = \begin{cases} 0.3 & x_4^3 = 7.1 \\ 0.25 & x_4^3 = 8.0 \\ 0.3 & x_4^3 = 8.5 \\ 0.15 & x_4^3 = 9.0 \end{cases},$$

$$g(\omega_1) = \begin{cases} 0.4 & \omega_1 = 0.1 \\ 0.3 & \omega_1 = 0.15 \\ 0.3 & \omega_1 = 0.2 \end{cases}, g(\omega_2) = \begin{cases} 0.2 & \omega_2 = 0.15 \\ 0.3 & \omega_2 = 0.2 \\ 0.5 & \omega_2 = 0.25 \end{cases},$$

$$g(\omega_3) = \begin{cases} 0.4 & \omega_3 = 0.2 \\ 0.2 & \omega_3 = 0.25 \\ 0.4 & \omega_3 = 0.3 \end{cases}, g(\omega_4) = \begin{cases} 0.45 & \omega_4 = 0.1 \\ 0.3 & \omega_4 = 0.12 \\ 0.25 & \omega_4 = 0.15 \end{cases}.$$

After both the distributed interval attribute values and distributed interval attribute weights have been constructed, according to the algorithm steps in Sec. 5, the decision-making process can proceed as follows.

Step 1. Use the operation rules of the DIWAA operator to calculate the distributed interval value of each alternative. Based on the complexity of this calculation process, we used the MATLAB software to perform calculations. The relevant results are provided below.

First, perform weighted calculation on each attribute value. Considering alternative P_1 as an example, we use the attribute value A_j^i ($1 \leq i \leq 3, 1 \leq j \leq 4$) and attribute weight ω_j ($1 \leq j \leq 4$). The results obtained are as follows:

$$T_{11}^* = \begin{bmatrix} 0.740 & 1.110 & 1.480 \\ 0.810 & 1.215 & 1.620 \\ 0.870 & 1.305 & 1.740 \end{bmatrix}. T_{12}^* = \begin{bmatrix} 1.080 & 1.440 & 1.800 \\ 1.140 & 1.520 & 1.900 \\ 1.290 & 1.720 & 2.150 \\ 1.350 & 1.800 & 2.250 \end{bmatrix}.$$

$$T_{13}^* = \begin{bmatrix} 1.460 & 1.825 & 2.190 \\ 1.620 & 2.025 & 2.430 \\ 1.740 & 2.175 & 2.610 \\ 1.780 & 2.225 & 2.670 \end{bmatrix}. T_{14}^* = \begin{bmatrix} 0.760 & 0.836 & 1.140 \\ 0.800 & 0.880 & 1.200 \\ 0.840 & 0.924 & 1.260 \\ 0.890 & 0.979 & 1.335 \end{bmatrix}$$

$$V_{11}^* = \begin{bmatrix} 0.100 & 0.075 & 0.075 \\ 0.160 & 0.120 & 0.120 \\ 0.140 & 0.105 & 0.105 \end{bmatrix}. V_{12}^* = \begin{bmatrix} 0.070 & 0.105 & 0.175 \\ 0.040 & 0.060 & 0.100 \\ 0.050 & 0.075 & 0.125 \\ 0.040 & 0.060 & 0.100 \end{bmatrix}$$

$$V_{13}^* = \begin{bmatrix} 0.100 & 0.050 & 0.100 \\ 0.100 & 0.050 & 0.100 \\ 0.120 & 0.060 & 0.120 \\ 0.080 & 0.040 & 0.080 \end{bmatrix}. V_{14}^* = \begin{bmatrix} 0.1125 & 0.075 & 0.0625 \\ 0.180 & 0.120 & 0.100 \\ 0.1125 & 0.075 & 0.0625 \\ 0.045 & 0.030 & 0.025 \end{bmatrix}.$$

Second, the cumulative distribution interval comprehensive scores of three potential green suppliers are obtained by integrating the weighted attribute values, which are assigned as follows:

$$z_1 = \{[4.040, 7.995], F_1\}$$

$$z_2 = \{[3.955, 8.020], F_2\}$$

$$z_3 = \{[3.940, 8.035], F_3\}.$$

Because of space limitations, the specific forms of the cumulative distribution $F_i (1 \leq i \leq 3)$ are not listed in detail.

Step 2. Calculate the normalized centroids of the cumulative distribution interval comprehensive scores for each alternative using Eqs. (10)–(13). The results are as follows:

$$zc_1 = (-1.3772, -0.5688),$$

$$zc_2 = (0.4104, 1.4057),$$

$$zc_3 = (0.9668, -0.8370).$$

Step 3. Calculate the ordinal distance matrix of the set of alternatives. The ordinal relationship matrix, distance matrix, and ordinal distance matrix between alternatives are defined as follows:

$$\bar{\omega} = \begin{bmatrix} 0 & -2 & -2 \\ 2 & 0 & -2 \\ 2 & 2 & 0 \end{bmatrix}, d = \begin{bmatrix} 0 & 2.6635 & 2.3594 \\ 2.6635 & 0 & 2.3107 \\ 2.3594 & 2.3107 & 0 \end{bmatrix},$$

$$L = \begin{bmatrix} 0 & -5.3270 & -4.7188 \\ 5.3270 & 0 & -4.6214 \\ 4.7188 & 4.6214 & 0 \end{bmatrix}.$$

Step 4. Calculate the relative dominance of the three alternatives. The results are $\bar{L}_1 = -10.0458, \bar{L}_2 = 0.7056,$ and $\bar{L}_3 = 9.3402.$ Therefore, the priority relationship $P_3 \succ P_2 \succ P_1$ among the alternatives is established. This means that the decision-maker should give priority to choosing green supplier three as a cooperative partner.

7. Conclusions

We designed a decision-making method based on attribute distribution information to select green suppliers by constructing distributed interval values. First, in the case of group decision-making, distributed interval attribute values and distributed interval attribute weights were obtained by means of experts quantifying the decision attribute values of potential green suppliers. Second, on the premise of the definition of the DIWAA operator and ranking rules, the relative dominance of each alternative was calculated separately to select a green supplier. This paper presented examples to demonstrate the feasibility and effectiveness of the proposed decision-making method based on distributed information for the issue of green supplier selection.

Unlike existing decision-making methods, the proposed method adopts the concept of modular computing and treats personal quantitative information in a group as a complete distribution. In the case where attributes and weights are both distributed interval values, decisions are made considering the differences in distribution characteristics between attribute values. The main advantage of this method is that it utilizes individual decision-making information fully and avoids information loss when integrating individual information into group information. Additionally, based on ranking rules and the relative dominance of cumulative distribution interval comprehensive decision values, the fusion of qualitative data and quantitative judgments can be realized, resulting in more reasonable results. Because this method does not make assumptions regarding the distributions of attributes but uses frequency distributions for calculation and cumulative distributions for comparison, it has strong application prospects and can be widely used in large-scale group decision-making and dynamic and repeated decision-making.

Disclosure statement

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