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Green Supplier Selection Using Improved TOPSIS and Best-Worst Method Under Intuitionistic Fuzzy Environment

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Abstract. Green supplier selection has recently become one of the key strategic considerations in green supply chain management, due to regulatory requirements and market trends. It can be regarded as a multi-criteria group decision-making (MCGDM) problem, in which a set of alternatives are evaluated with respect to multiple criteria. MCGDM methods based on Analytic Hierarchy Process (AHP) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) are widely used in solving green supplier selection problems. However, the classic AHP must conduct large amounts of pairwise comparisons to derive a consistent result due to its complex structure. Meanwhile, the classic TOPSIS only considers one single negative idea solution in selecting suppliers, which is insufficiently cautious. In this study, an improved TOPSIS integrated with Best-Worst Method (BWM) is developed to solve MCGDM problems with intuitionistic fuzzy information in the context of green supplier selection. The BWM is investigated to derive criterion weights, and the improved TOPSIS method is proposed to obtain decision makers' weights in terms of different criteria. Moreover, the developed TOPSIS-based coefficient is used to rank alternatives. Finally, a green supplier selection problem in the agri-food industry is presented to validate the proposed approach followed by sensitivity and comparative analyses.

Key words: supplier selection, group decision-making, best-worst method, intuitionistic fuzzy sets.

1. Introduction

In recent years, governments and industries have been attempting to decouple economic growth from commensurate environmental burdens (Vazquez-Brust and Sarkis, 2012). An increasing number of consumers prefer green products because of the rise of public consciousness in environmental protection (Fahimnia *et al.*, 2015b). Facing the changes in consumer requirements and government policies for environment-sustainable development has become a significant issue in modern production operation management. Green supply chain management allowing for environment performance is regarded as an innovative management mode. This management mode involves several core links, such as green

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supplier evaluation and selection, green product design, green production, green packaging and transportation, green marketing and resource recycling (Fahimnia *et al.*, 2015a). Green supplier is the enterprise that holds sustainable development as its responsibility and integrates environmental benefits and management into the entire process of enterprise management to provide eco-friendly products and services to its partners (Fahimnia *et al.*, 2015a).

Green suppliers are located upstream of the entire supply chain; thus, they can effectively help enterprises move towards a green supply chain design (Blome *et al.*, 2014). Green supplier selection requires the incorporation of environmental criteria into the traditional supplier selection practices, and is commonly viewed as a multi-criteria group decision-making (MCGDM) problem that selects the optimal alternative in terms of a set of economic and environmental criteria (Govindan *et al.*, 2015). Practically, in the green supplier selection process, experts with different knowledge backgrounds often express disagreement in evaluation. As a result, methodologies based on traditional fuzzy sets might be insufficient to model practical situations because of the increasing complexity of the decision-making environment. Moreover, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) structure (Hwang and Yoon, 1981) is one of the most effective methods for ranking alternatives (Zyoud and Fuchs-Hanusch, 2017). Chu *et al.* (2007) revealed that in comparison with traditional methods TOPSIS inherited better distinguishing capability for describing assessment results, such as a simple additive weighing approach, because of its outstanding characteristics, such as straightforward computation, logical and rational procedures and incorporation of relative criterion weights (Mufazzal and Muzakkir, 2018). Recently, TOPSIS and fuzzy TOPSIS associated with other methods have been successfully used to solve green supplier evaluation and selection problems (Govindan *et al.*, 2015). However, the conventional TOPSIS method adopts only a single negative ideal decision (NID) in the core structure, which is insufficiently cautious in addressing complex MCGDM problems that involve multiple experts (Yue, 2014). Thus, some improved MCGDM approaches for supplier selection are needed.

The present work attempts to remedy the limitations of existing studies and develops a hybrid MCGDM method for green supplier selection within the context of intuitionistic fuzzy sets (IFSs). The innovation and contribution of this study are three-fold. Firstly, IFSs (Atanassov, 1986) are used to capture decision-makers (DMs)' agreements and disagreements when eliciting evaluations in the green supplier selection process. Secondly, the proposed approach combines the Best-Worst Method (BWM) and improved TOPSIS. The BWM (Rezaei, 2015) is used to obtain the subjective weights of criteria due to its low calculation complexity in obtaining consistent comparisons. The improved TOPSIS associated with multiple NIDs (Yue, 2014) is constructed to derive DMs' weights and rank alternatives. The weight information of DMs with respect to different criteria can be objectively obtained. Meanwhile, the ranking of all the alternatives can be achieved through a comprehensive TOPSIS-based index. Lastly, the proposed hybrid MCGDM method is applied to manage an actual green supplier selection problem.

The remainder of this study is organized as follows. Section 2 presents the current research state on intuitionistic fuzzy TOPSIS method, BWM and green supplier selection methods. Section 3 comprehensively explains the developed methodology and describes its steps. Section 4 presents an application of the proposed approach. Section 5 conducts sensitivity and comparative analyses to verify the priority of the proposed method. Section 6 provides the conclusions.

2. Literature Review

2.1. *Intuitionistic Fuzzy TOPSIS Methods*

In real life, DMs frequently disagree when expressing their ideas in assessment. Fuzzy sets (Zadeh, 1965) can only depict fuzziness of agreement but not reflect the disagreement of DMs, while IFSs (Atanassov, 1986) are an appropriate tool for describing DMs' agreement and disagreement evaluations. In the recent decades, IFSs have been widely used in managing fuzziness in DMs' assessments in complex socioeconomic situations (Kahraman *et al.*, 2016).

TOPSIS developed by Hwang and Yoon (1981) is one of the widely recognized multi-criteria decision-making (MCDM) methods (Zavadskas *et al.*, 2016). TOPSIS is established on the basis of the principle that the optimal solution should be closest to the positive ideal point and farthest to the negative ideal point (Aouadni *et al.*, 2017; Dwivedi *et al.*, 2018; Opricovic and Tzeng, 2004). Recently, numerous researchers have extended TOPSIS to solve intuitionistic fuzzy MCDM problems (Chen *et al.*, 2016; Shen *et al.*, 2018; Wan *et al.*, 2015; Yue, 2014). Furthermore, TOPSIS has been integrated with other methods. Li and Wu (2016) proposed an improved interval-valued intuitionistic fuzzy TOPSIS integrated with a cumulative interval score function and applied it to manage MCDM problems with unknown weight information. Aloini *et al.* (2014) developed a peer-based modification to intuitionistic fuzzy MCGDM with TOPSIS and used it in packaging machine selection. Buyukozkan and Guleryuz (2016) established an integrated intuitionistic fuzzy MCGDM approach associated with Analytical Hierarchy Process (AHP) and TOPSIS and employed it to select a suitable product development partner.

2.2. *BWM*

The BWM proposed by Rezaei (2015) is a comparison-based method that establishes specific comparisons between items. For a comparison issue that contains n items, firstly, the best and worst items are determined, and the important degree of the best item to the worst one is then evaluated. Secondly, comparisons between the remaining $n-2$ items and the best and worst items are needed. Lastly, a mathematical program model is constructed to derive the important values of items. In comparison with the traditional AHP (Saaty, 1980) and Analytical Network Process (ANP) (Saaty, 1996), BWM only requires to conduct $2n-3$ comparisons. Statistical finding shows that BWM requires less comparison data but results in more consistent comparisons (Rezaei, 2016). To extend BWM to an uncertain environment, Mou *et al.* (2016) developed an intuitionistic fuzzy multiplicative BWM and applied it to MCGDM. Li *et al.* (2018) proposed a BWM method and used it in MCDM with probabilistic hesitant fuzzy information. Moreover, BWM was applied to supplier segmentation (Rezaei *et al.*, 2015), water security sustainability evaluation (Nie *et al.*, 2018a), failure mode and effects analysis (Nie *et al.*, 2018b; Tian *et al.*, 2018a) and performance evaluation of smart bike-sharing programs (Tian *et al.*, 2018b).

2.3. *Green Supplier Selection Methods*

Numerous researchers have studied the criteria and decision models involved in the process of selecting a suitable supplier (Chai *et al.*, 2013). An increasing number of enterprises incorporate the green concept into the supplier chain management to comply with the trend of sustainable development. Numerous studies have focused on green supplier selection problems that allow for a set of conventional and environmental criteria (Beske *et al.*, 2014; Govindan *et al.*, 2015). In this regard, Govindan *et al.* (2015) found that environmental management system (EMS) was the most significant and comprehensive environmental criterion in the process of evaluating enterprises' environmental performance and operation efficiency. Banaeian *et al.* (2015) identified EMS as a green criterion and financial, delivery and service and qualitative as the primary conventional criteria associated with a set of sub-criteria. These criteria were applied to select a green supplier in the food industry.

Recently, large numbers of green supplier evaluation and selection approaches have been developed, ranging from a single method to hybrid methods that are integrated with multiple techniques (Govindan *et al.*, 2015). Dobos and Vorosmarty (2014) used Data Envelopment Analysis (DEA) as an evaluation tool. Dou *et al.* (2014) and Hashemi *et al.* (2015) combined ANP and Grey Relational Analysis (GRA) and applied them to evaluate green supplier development programs. Kuo *et al.* (2015) employed DEMATEL (DEcision MAking Trial and Evaluation Laboratory) associated with ANP to determine criterion value and VIKOR (VIsekriterijumska optimizacija I KOmpromisno Resenje) to evaluate the environmental performance of suppliers in the electronic industry. Banaeian *et al.* (2014) proposed a hybrid model using Delphi and DEA. Tsui *et al.* (2015) developed a hybrid MCDM method using DEMATEL, ANP and PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) for green supplier selection. Freeman and Chen (2015) presented a comprehensive framework integrated with AHP, entropy and TOPSIS. Vahidi *et al.* (2018) developed a novel bi-objective two-stage mixed possibilistic-stochastic programming model to manage green supplier selection.

However, in green supplier evaluation and selection processes, some criteria are often precisely unknown, especially for environmental factors, such as easy recycling and reuse capability. Under this environment, fuzzy set theory can be regarded as an effective tool for addressing uncertainty. Kannan *et al*. employed a fuzzy TOPSIS method to select green suppliers for a Brazilian electronics company (Kannan *et al.*, 2014). They also developed a fuzzy axiomatic design to select green suppliers for a Singapore plastic manufacturing company (Kannan *et al.*, 2015). Akman (2015) combined the fuzzy c-means

Table 1
Summary of studies using decision-making methods for green supplier selection.

Category	Method	MCGDM	Industry	Literature
Optimization model	DEA			Dobos and Vorosmarty (2014)
	Bi-objective programming		Automotive industry	Vahidi *et al.* (2018)
Fuzzy clustering	Fuzzy c-means and VIKOR		Automotive industry	Akman (2015)
MCDM model	ANP and GRA; fuzzy NGT and VIKOR; fuzzy ANP, DEMATEL and TOPSIS; fuzzy TODIM; fuzzy QUALIFLEX	Yes	Automotive industry	Hashemi *et al.* (2015), Awasthi and Kannan (2016), Buyukozkan and Cifci (2012), Qin *et al.* (2017), Li and Wang (2017)
	ANP, DEMATEL and VIKOR; AHP, entropy and TOPSIS; fuzzy TOPSIS	Yes	Electronic industry	Kuo *et al.* (2015), Freeman and Chen (2015), Kannan *et al.* (2014)
	Delphi and DEA; fuzzy TOPSIS, VIKOR and GRA	Yes	Food industry	Banaeian *et al.* (2014), Banaeian *et al.* (2018)
	ANP and GRA		Pivot irrigation equipment industry	Dou *et al.* (2014)
	Fuzzy axiomatic design		Engineering plastic material industry	Kannan *et al.* (2015)
	Fuzzy WASPAS	Yes		Ghorabaee *et al.* (2016)
	DEMATEL, ANP and PROMETHEE	Yes	Polariser industry	Tsui *et al.* (2015)
	Fuzzy AHP and TOPSIS	Yes	Fashion industry	Wang and Chan (2013)
	Fuzzy AHP, ARAS and MSGP	Yes	Light industrial machinery industry	Liao *et al.* (2016)

clustering and fuzzy VIKOR methods. Awasthi and Kannan (2016) incorporated the fuzzy Nominal Group Technique (NGT) with fuzzy VIKOR methods for green supplier development. Wang and Chan (2013) integrated the fuzzy AHP with fuzzy TOPSIS to support green supply chain management. Furthermore, fuzzy hybrid MCDM methods with multiple techniques, such as fuzzy ANP, DEMATEL and TOPSIS (Buyukozkan and Cifci, 2012), fuzzy AHP, Additive Ratio Assessment (ARAS) and Multi-Segment Goal Programming (MSGP) (Liao *et al.*, 2016), and fuzzy TOPSIS, VIKOR and GRA (Banaeian *et al.*, 2018) were developed. Interval type-2 fuzzy MCGDM methods based on Weighted Aggregated Sum Product Assessment (WASPAS) (Ghorabaee *et al.*, 2016) and TODIM (An Acronym in Portuguese of Interactive and MCDM) (Qin *et al.*, 2017), and probability hesitant fuzzy QUALIFLEX (QUALItative FLEXible Multiple Criteria Method) (Li and Wang, 2017) were proposed to manage green supplier selection. Table 1 presents a summary of preceding literature on green supplier selection.

As shown in Table 1, fuzzy set theory equipped with MCGDM methods has been applied to solve green supplier selection problems. However, minimal attention has been paid to intuitionistic fuzzy environment to address multi-criteria green supplier evaluation and selection problems. Furthermore, AHP and ANP methods are often employed to obtain criterion weights in green supplier selection. However, they may be tedious and complex in calculation to achieve consistent comparisons. The MCGDM methods with TOPSIS are used to rank green suppliers. The decision process is insufficiently cautious because DMs with different knowledge backgrounds are assigned with the same weights with respect to different criteria.

3. Proposed Methodology

This section introduces the methodology used in this study for solving green supplier selection problems. Some concepts of IFSs are presented, followed by the developed methodology and steps.

3.1. *Preliminaries*

Definition 1. (See Atanassov, 1986.) Let X be a fixed set. An IFS is denoted by:

$$A = \big\{\langle x, \mu_A(x), \nu_A(x)\rangle \big| x \in X.\big\},$$

where $\mu_A(x) \in [0, 1]$ and $\nu_A(x) \in [0, 1]$ are characterized by membership and non-membership functions, respectively, satisfying the condition $0 \leqslant \mu_A(x) + \nu_A(x) \leqslant 1$ for any $x \in X$. Moreover, $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ indicates a hesitancy function.

For an IFS $\{\langle x, \mu_A(x), \nu_A(x)\rangle | x \in X.\}$, the ordered tuple components $\langle \mu_A(x), \nu_A(x)\rangle$ are described as intuitionistic fuzzy numbers (IFNs). Any IFN $\langle \mu, \nu\rangle$ must satisfy the conditions $\mu, \nu \in [0, 1]$ and $0 \leqslant \mu + \nu \leqslant 1$.

Definition 2. (See Atanassov, 1994; Xu, 2007.) Let $a_j = \langle \mu_{a_j}, \nu_{a_j}\rangle$ $(j = 1, 2)$ be any two IFNs. Then, (1) $a_1 \oplus a_2 = \langle \mu_{a_1} + \mu_{a_2} - \mu_{a_1}\mu_{a_2}, \nu_{a_1}\nu_{a_2}\rangle$; (2) $\lambda a_1 = \langle 1 - (1 - \mu_{a_1})^\lambda, \nu_{a_1}^\lambda\rangle$, $\lambda \geqslant 0$; (3) $a_1^c = \langle \nu_{a_1}, \mu_{a_1}\rangle$, where a_1^c is the complement of a_1.

Definition 3. (See Xu, 2007.) Let $a_j = \langle \mu_{a_j}, \nu_{a_j}\rangle$ $(j = 1, 2)$ be two IFNs. Moreover, let $S(a_j) = \mu_{a_j} - \nu_{a_j}$ and $H(a_j) = \mu_{a_j} + \nu_{a_j}$ be the score and accuracy functions of a_j $(j = 1, 2)$, respectively. Then,

(1) If $S(a_1) < S(a_2)$, then a_1 is inferior to a_2, denoted by $a_1 < a_2$;
(2) If $S(a_1) < S(a_2)$, then
  (i) If $H(a_1) = H(a_2)$, then a_1 is equal to a_2, denoted by $a_1 = a_2$;
  (ii) If $H(a_1) < H(a_2)$, then a_1 is inferior to a_2, denoted by $a_1 < a_2$.

Definition 4. (See Xu, 2007.) Let $a_j = \langle \mu_{a_j}, \nu_{a_j}\rangle$ $(j = 1, 2, \dots, n)$ be a collection of IFNs. An intuitionistic fuzzy ordered weighted average (IFOWA) operator is a mapping *IFOWA*: $\Omega^n \to \Omega$ and is defined as follows:

$$IFOWA(a_1, a_2, \dots, a_n) = \sum_{j=1}^{n} \varpi_j a_{\sigma(j)} = \left\langle 1 - \prod_{j=1}^{n} (1 - \mu_{\sigma(j)})^{\varpi_j}, \prod_{j=1}^{n} \nu_{\sigma(j)}^{\varpi_j} \right\rangle, \tag{1}$$

where $(\sigma(1), \sigma(2), \ldots, \sigma(n))$ is a permutation of $(1, 2, \ldots, n)$, such that $a_{\sigma(j-1)} \geqslant a_{\sigma(j)}$ for all j. $\varpi = (\varpi_1, \varpi_2, \ldots, \varpi_n)$ represents the associated weight vector, where $\varpi_j \geqslant 0$ and $\sum_{j=1}^{n} \varpi_j = 1$.

Definition 5. (See Szmidt and Kacprzyk, 2000; Yu *et al.*, 2018.) Let $a_j = \langle \mu_{a_j}, \nu_{a_j} \rangle$ $(j = 1, 2)$ be any two IFNs. The Euclidean distance between a_1 and a_2 is defined as follows:

$$d(a_1, a_2) = \sqrt{\frac{1}{2}\big((\mu_1 - \mu_2)^2 + (\nu_1 - \nu_2)^2 + (\pi_1 - \pi_2)^2\big)}, \tag{2}$$

where $\pi_1 = 1 - \mu_1 - \nu_1$ and $\pi_2 = 1 - \mu_2 - \nu_2$.

The Euclidean distance between two intuitionistic fuzzy matrices can be defined as follows:

Definition 6. (See Yue, 2014.) Let $A_k = (\langle \mu_{ij}^k, \nu_{ij}^k \rangle)_{m \times n}$ $(k = 1, 2)$ be two intuitionistic fuzzy matrices, where the elements in A_k are IFNs. Then, the distance between A_1 and A_2 is defined as follows:

$$d(A_1, A_2) = \sqrt{\frac{1}{2mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \big(\big(\mu_{ij}^1 - \mu_{ij}^2\big)^2 + \big(\nu_{ij}^1 - \nu_{ij}^2\big)^2 + \big(\pi_{ij}^1 - \pi_{ij}^2\big)^2\big)}, \tag{3}$$

where $\pi_{ij}^1 = 1 - \mu_{ij}^1 - \nu_{ij}^1$ and $\pi_{ij}^2 = 1 - \mu_{ij}^2 - \nu_{ij}^2$ $(i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n)$.

3.2. *Steps of the Integrated Methodology*

This subsection presents an integrated methodology for green supplier selection on the basis of BWM and improved TOPSIS. Figure 1 shows the flowchart of the proposed approach.

For convenience, let $M = \{1, 2, \ldots, m\}$, $N = \{1, 2, \ldots, n\}$ and $T = \{1, 2, \ldots, t\}$. The MCGDM problem concerned is described as follows.

Let $A = \{a_1, a_2, \ldots, a_m\}$ be a set of m alternatives, $C = \{c_1, c_2, \ldots, c_n\}$ be a set of n criteria, and $E = \{e_1, e_2, \ldots, e_t\}$ be a set of t DMs. Assume that w_j $(j \in N)$ is the weight value of c_j, where $w_j \geqslant 0$ and $\sum_{j=1}^{n} w_j = 1$. Suppose that r_{ij}^k $(i \in M,\ j \in N,\ k \in T)$ represents the rating of alternative a_i with respect to criterion c_j provided by DM e_k. Thus, the individual decision matrix provided by DM e_k can be expressed as $R^k = (r_{ij}^k)_{m \times n}$. Denote the weight vector of criteria by $w = (w_1, w_2, \ldots, w_n)$, and the weight vector of DMs by $\omega = (\omega_1, \omega_2, \ldots, \omega_t)$.

The focus is how to rank alternatives on the basis of individual decision matrices R^k $(k \in T)$ associated with weight information. To solve this type of MCGDM problem, a methodology integrated with intuitionistic fuzzy TOPSIS and BWM is introduced. The main steps of the proposed approach are briefly presented as follows.

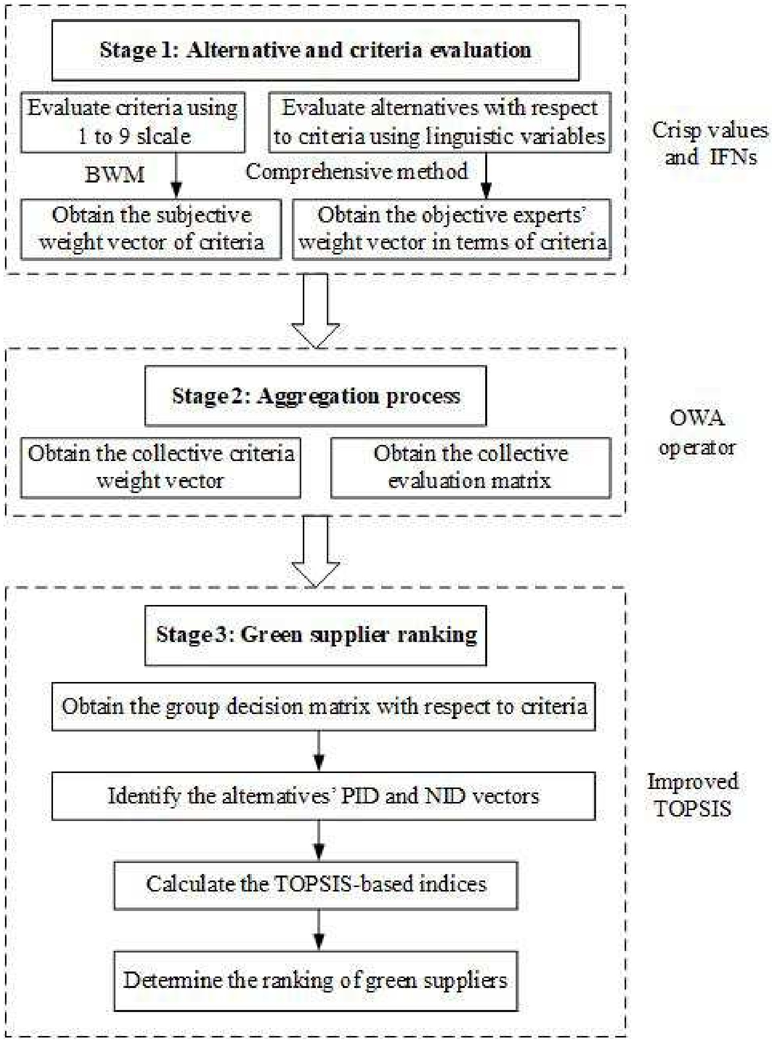

Fig. 1. Assessment framework of the proposed approach.

Step 1: Define the overall goal, criteria, sub-criteria and associated alternatives for decision-making problems, and then establish the hierarchy of the considered problem.

Step 2: Design and select the evaluation scale of IFS.
The study by Aloini *et al.* (2014) is employed to assign the evaluation values of alternatives by using the scale, as shown in Table 2.

Step 3: Determine the weight vectors of criteria and sub-criteria.

In accordance with the principle of BWM developed by Rezaei (2015, 2016), DMs firstly select the best (e.g. most important and desirable) and the worst (e.g. least important and desirable) criteria.

Table 2
Rating alternatives with linguistic terms (Aloini *et al.*, 2014).

Linguistic terms	IFNs
Absolutely good (AG)/absolutely high (AH)	$\langle 0.9, 0.05, 0.05\rangle$
Very good (VG)/very high (VH)	$\langle 0.8, 0.1, 0.1\rangle$
Good (G)/high (H)	$\langle 0.7, 0.2, 0.1\rangle$
Medium good (MG)/medium high (MH)	$\langle 0.6, 0.3, 0.1\rangle$
Fair (F)/medium (M)	$\langle 0.45, 0.4, 0.15\rangle$
Medium poor (MP)/medium low (ML)	$\langle 0.4, 0.5, 0.1\rangle$
Poor (P)/low (L)	$\langle 0.3, 0.6, 0.1\rangle$
Very poor (VP)/very low (VL)	$\langle 0.2, 0.7, 0.1\rangle$
Absolutely poor (AP)/absolutely low (AL)	$\langle 0.05, 0.9, 0.05\rangle$

Secondly, DMs determine the preferences of the best criterion over all the other criteria by using a number from 1 to 9 (1 means equally important and 9 signifies extremely important). The result is presented as a 'best-to-others (BO)' vector as follows:

$$U_B = (u_{B1}, u_{B2}, \dots, u_{Bn}),$$

where u_{Bj} indicates the preference of the best criterion B over criterion j, and $u_{BB} = 1$.

Thirdly, DMs determine the preferences of the other criteria over the worst criterion by using a number from 1 to 9 (1 means equally important and 9 signifies extremely important). The result is presented as an 'others-to worst (OW)' vector as follows:

$$V_W = (v_{1W}, v_{2W}, \dots, v_{nW})^T,$$

where v_{jW} indicates the preference of criterion j over the worst criterion W, and $v_{WW} = 1$.

Lastly, establish a mathematical model and derive the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$. For each pair of w_B/w_j and w_j/w_W, the optimal weight should satisfy the conditions $w_B/w_j = u_{Bj}$ and $w_j/w_W = v_{jW}$. To meet these requirements, the maximum absolute differences $|\frac{w_B}{w_j} - u_{Bj}|$ and $|\frac{w_j}{w_W} - v_{jW}|$ for all j should be minimized. Thus, the following model can be constructed by considering the sum condition and non-negativity of weights.

$$\begin{aligned} &\min \max_j \left\{ \left| \frac{w_B}{w_j} - u_{Bj} \right|, \left| \frac{w_j}{w_W} - v_{jW} \right| \right\} \\ &108pt]\text{s.t.} \begin{cases} w_j \geqslant 0, \quad \text{forall } j \\ \sum_{j=1}^n w_{j=1}. \end{cases} \end{aligned} \tag{4}$$

Table 3
Consistency index of BWM (Rezaei, 2015).

	1	2	3	4	5	6	7	8	9
Consistency index	0.00	0.44	1.00	1.63	2.33	3.00	3.73	4.47	5.23

Here, Model (4) can be transformed into the following linear programming model:

$$\min \xi \\ \text{s.t.} \begin{cases} \left|\frac{w_B}{w_j} - u_{Bj}\right| \leqslant \xi, & \text{for all } j \\ \left|\frac{w_j}{w_W} - v_{jW}\right| \leqslant \xi, & \text{for all } j \\ w_j \geqslant 0, & \text{for all } j \\ \sum_{j=1}^{n} w_j = 1. \end{cases} \tag{5}$$

The optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$ and consistency index ξ^* can be derived by solving Model (5). Furthermore, calculating the consistency level of comparisons is required. Rezaei (2015) defined the consistency index as follows.

Definition 7. (See Rezaei, 2015.) A comparison is fully consistent when $v_{Bj} \times v_{jW} = v_{BW}$ for all j, in which v_{Bj}, v_{jW} and v_{BW} indicate the preference of the best criterion over criterion j, the preference of criterion j over the worst criterion and the preference of the best criterion over the worst criterion, respectively.

The consistency ratio (CR) of the BWM can be calculated, combining the obtained ξ^* and its corresponding consistency index (Table 3) as follows:

$$CR = \frac{\xi^*}{\text{Consistency index}}, \tag{6}$$

where $CR \in [0, 1]$. The closer the CR is to zero, the more consistent the obtained vector will be, and vice versa. Generally, $CR \leqslant 0.1$ shows that the obtained vector is acceptable.

Step 4: Determine DMs' weights with respect to different criteria.

As every DM is skilled in only some specific fields, it is more appropriate to allocate different weight values of each DM on different criteria.

For each criterion c_j, the criterion value expressed by DM e_k is transformed into an IFN vector $r_j^k = (r_{1j}^k, r_{2j}^k, \ldots, r_{mj}^k)$. Let ω_j^k be the weight of e_k with respect to c_j. To determine the criterion weight ω_j^k, two aspects should be considered simultaneously. One aspect is the closeness coefficient that captures the similarity between the individual decision matrix provided by DM e_k and the collective one by the group of DMs. The other aspect is the proximity degree that measures the proximity between the individual decision matrix provided by DM e_k and those matrices provided by all other DMs.

In accordance with the previous analysis, ω_j^k $(j \in N;\ k \in T)$ can be derived from two aspects. On one hand, an improved TOPSIS method inspired by the idea of TOPSIS

(Hwang and Yoon, 1981; Wang *et al.*, 2017; Yue, 2014) is developed to calculate the closeness coefficient. On the other hand, the proximity degree can be calculated on the basis of distance measure.

(1) Calculate the closeness coefficient on the basis of the improved TOPSIS.

(i) Determine the positive ideal decision (PID) vector r_j^* on criterion c_j.

The PID vector r_j^* on criterion c_j is defined as the arithmetic average of all individual decision vectors r_j^k $(k \in T)$ on the basis of Eq. (1), that is, $r_j^* = (r_{1j}^*, r_{2j}^*, \dots, r_{mj}^*)$, where

$$\begin{aligned} r_{ij}^* &= \langle \mu_{ij}^*, \nu_{ij}^* \rangle = IFOWA\big(r_{ij}^1, r_{ij}^2, \dots, r_{ij}^t\big) \\ &= \left\langle 1 - \prod_{k=1}^{t} \big(1 - \mu_{ij}^{\sigma(k)}\big)^{\varpi_k}, \prod_{k=1}^{t} \big(\nu_{ij}^{\sigma(k)}\big)^{\varpi_k} \right\rangle \quad (i \in M,\ j \in N), \end{aligned} \tag{7}$$

where ϖ_k is the associated weight value of the IFOWA operator, and its value can be determined in accordance with the normal distribution-based method (Xu, 2005).

(ii) Determine all the NID vectors on criterion c_j.

The NID vectors consist of the individual negative ideal decision (INID) vector, left individual negative ideal decision (LINID) vector and right individual negative ideal decision (RINID) vector. The INID, LINID and RINID vectors on criterion c_j are denoted by $r_j^c = (r_{1j}^c, r_{2j}^c, \dots, r_{mj}^c)$, $r_j^{l-} = (r_{1j}^{l-}, r_{2j}^{l-}, \dots, r_{mj}^{l-})$ and $r_j^{r-} = (r_{1j}^{r-}, r_{2j}^{r-}, \dots, r_{mj}^{r-})$, respectively. In accordance with the complement operation in Definition 2,

$$\begin{aligned} r_{ij}^c &= \langle \mu_{ij}^c, \nu_{ij}^c \rangle, \quad \text{where } \mu_{ij}^c = \nu_{ij}^* = \prod_{k=1}^{t} \big(\nu_{ij}^{\sigma(k)}\big)^{\varpi_k} \quad \text{and} \\ \nu_{ij}^c &= \mu_{ij}^* = 1 - \prod_{k=1}^{t} \big(1 - \mu_{ij}^{\sigma(k)}\big)^{\varpi_k}, \end{aligned} \tag{8}$$

$$r_{ij}^{l-} = \langle \mu_{ij}^{l-}, \nu_{ij}^{l-} \rangle, \quad \text{where } \mu_{ij}^{l-} = \min_{k \in T} \{\mu_{ij}^k\} \quad \text{and} \quad \nu_{ij}^{l-} = \max_{k \in T} \{\nu_{ij}^k\}, \tag{9}$$

$$r_{ij}^{r-} = \langle \mu_{ij}^{r-}, \nu_{ij}^{r-} \rangle, \quad \text{where } \mu_{ij}^{r-} = \max_{k \in T} \{\mu_{ij}^k\} \quad \text{and} \quad \nu_{ij}^{r-} = \min_{k \in T} \{\nu_{ij}^k\}. \tag{10}$$

(iii) Calculate distances $d(r_j^k, r_j^*)$, $d(r_j^k, r_j^c)$, $d(r_j^k, r_j^{l-})$ and $d(r_j^k, r_j^{r-})$ by using Eq. (3).

Subsequently, an extended closeness coefficient of each individual decision vector r_j^k with respect to the ideal decision vectors, including r_j^*, r_j^c, r_j^{l-} and r_j^{r-}, is defined as follows:

$$\varphi_j^k = \frac{d(r_j^k, r_j^c) + d(r_j^k, r_j^{l-}) + d(r_j^k, r_j^{r-})}{d(r_j^k, r_j^*) + d(r_j^k, r_j^c) + d(r_j^k, r_j^{l-}) + d(r_j^k, r_j^{r-})} \quad (j \in N,\ k \in T). \tag{11}$$

(2) Calculate the average proximity degree on the basis of distance measure.

The proximity degree between r_{ij}^k and r_{ij}^l is denoted by γ_{ij}^{lk} and can be calculated as:

$$\gamma_{ij}^{lk} = 1 - d\big(r_{ij}^l, r_{ij}^k\big), \tag{12}$$

where $d(r_{ij}^l, r_{ij}^k)$ is the distance between r_{ij}^k and r_{ij}^l on the basis of Eq. (2).

Furthermore, on the basis of Eq. (12), the average proximity degree η_j^k between DM e_k and all the other DMs e_l $(l \in T, l \neq k)$ on criterion c_j can be calculated as follows:

$$\eta_j^k = \frac{1}{m(t-1)} \sum_{l=1, l\neq k}^{t} \sum_{i=1}^{m} \gamma_{ij}^{lk} = 1 - \frac{1}{m(t-1)} \sum_{l=1, l\neq k}^{t} \sum_{i=1}^{m} d\big(r_{ij}^l, r_{ij}^k\big), \tag{13}$$

where $d(r_{ij}^l, r_{ij}^k)$ is the distance between r_{ij}^k and r_{ij}^l on the basis of Eq. (2).

(3) Derive the weights of DMs with respect to different criteria.

To comprehensively consider the closeness coefficient and proximity degree, a control parameter θ $(0 \leqslant \theta \leqslant 1)$ is employed to construct the unified criterion weight λ_j^k of DM e_k on criterion c_j, as shown as follows:

$$\lambda_j^k = \theta\varphi_j^k + (1-\theta)\eta_j^k. \tag{14}$$

The unified criterion weight λ_j^k can tradeoff the closeness efficient versus the proximity degree by altering the values of parameter θ. Particularly, λ_j^k will only depend on the closeness efficient if $\theta = 1$, and it will only depend on the proximity degree if $\theta = 0$. Without loss of generality, a default control parameter $\theta = 0.5$ can be set in practical application.

The unified criterion weights λ_j^k $(k \in T)$ are normalized, and the weight ω_j^k of DM e_k with respect to criterion c_j can be obtained as follows:

$$\omega_j^k = \frac{\lambda_j^k}{\sum_{l=1}^{t} \lambda_j^l} \quad (j \in N,\ k \in T). \tag{15}$$

Let $\hat{R}^k = (\hat{r}_{ij}^k)_{m\times n}$ be the weighted individual decision matrix. Then, the following result can be obtained:

$$\hat{R}^k = \big(\hat{r}_{ij}^k\big)_{m\times n} = \big(\omega_j^k r_{ij}^k\big)_{m\times n} = \big(\langle\hat{\mu}_{ij}^k, \hat{\nu}_{ij}^k\rangle\big)_{m\times n} \quad (k \in T), \tag{16}$$

where $\hat{\mu}_{ij}^k = 1 - (1-\mu_{ij}^k)^{\omega_j^k}$ and $\hat{\nu}_{ij}^k = (\nu_{ij}^k)^{\omega_j^k}$ on the basis of the operations in Definition 2. ω_j^k denotes the obtained weight of DM e_k using Eq. (15).

Step 5: Rank all the alternatives and select the optimal one (s).

In the following, the target is to rank all the alternatives on the basis of the improved TOPSIS method.

(1) Obtain the group decision matrix with respect to criteria.

For each alternative a_i $(i \in M)$, the weighted individual decision matrix in Eq. (16) is transformed into a group decision matrix of DMs with respect to the following criteria:

$$H^i = (h^i_{kj})_{t\times n} = \left(\langle \hat{\mu}^i_{kj}, \hat{\nu}^i_{kj}\rangle\right)_{t\times n} \quad (i \in M), \tag{17}$$

where the element h^i_{kj} in H^i is the same as the element $\hat{r}^k_{ij}$ in $\hat{R}^k$ in Eq. (16). Similar to the individual decision matrix R^k, the matrix H^i is called the alternative decision matrix. For each criterion c_j, the weighted criterion values of alternative a_i expressed by all the DMs e_k $(k \in T)$ are denoted as an IFN vector $h^i_j = (h^i_{1j}, h^i_{2j}, \dots, h^i_{tj})$.

(2) Determine the alternatives' PID vector h^*_j and the NID vectors h^c_j and h^-_j on criterion c_j.

Similar to the procedures in Step 4, let $h^*_j = (h^*_{1j}, h^*_{2j}, \dots, h^*_{tj})$ denote the alternatives' PID vector. The alternatives' PID vector should be the best decision of all H^i $(i \in M)$ in Eq. (17). The elements in the alternatives' PID vector can be calculated as follows:

$$h^*_{kj} = \langle \hat{\mu}^*_{kj}, \hat{\nu}^*_{kj}\rangle, \quad \text{where } \hat{\mu}^*_{tj} = \max_{i\in M}\left\{\hat{\mu}^i_{kj}\right\} \quad \text{and} \quad \hat{\nu}^*_{kj} = \min_{i\in M}\left\{\hat{\nu}^i_{kj}\right\}. \tag{18}$$

Similar to the individual NID decision vectors, the alternatives' NID vector should have maximum separation from the alternatives' PID vector h^*_j. It can naturally consider the complement $(h^*_j)^c$ of h^*_j, which shows the maximum separation from h^*_j. Let $h^c_j = (h^c_{1j}, h^c_{2j}, \dots, h^c_{tj})$ denote the complement $(h^*_j)^c$ of h^*_j, where

$$h^c_{kj} = \langle \hat{\mu}^c_{kj}, \hat{\nu}^c_{kj}\rangle, \quad \text{where } \hat{\mu}^c_{kj} = \hat{\nu}^*_{kj} = \min_{i\in M}\left\{\hat{\nu}^i_{kj}\right\} \quad \text{and} \quad \hat{\nu}^c_{kj} = \hat{\mu}^*_{kj} = \max_{i\in M}\left\{\hat{\mu}^i_{kj}\right\}. \tag{19}$$

Moreover, the following alternatives' decision vector also shows the maximum separation from the alternatives' PID vector h^*_j. Let $h^-_j = (h^-_{1j}, h^-_{2j}, \dots, h^-_{tj})$ denote one of the alternatives' NID vectors, where

$$h^-_{kj} = \langle \hat{\mu}^-_{kj}, \hat{\nu}^-_{kj}\rangle, \quad \text{where } \hat{\mu}^-_{kj} = \min_{i\in M}\left\{\hat{\mu}^i_{kj}\right\} \quad \text{and} \quad \hat{\nu}^-_{kj} = \max_{i\in M}\left\{\hat{\nu}^i_{kj}\right\}. \tag{20}$$

(3) Calculate the TOPSIS-based index CI^i_{kj} and the comprehensive TOPSIS-based index $CI(a_i)$.

The distances between each alternative's decision value h^i_{kj} and h^*_{kj}, h^c_{kj} and h^-_{kj} are calculated on the basis of Eq. (2) and are denoted as $d(h^i_{kj}, h^*_{kj})$, $d(h^i_{kj}, h^c_{kj})$ and $d(h^i_{kj}, h^-_{kj})$, respectively.

Furthermore, an improved TOPSIS-based index is developed to measure the discrimination of h^i_{kj} with respect to h^*_{kj}, h^c_{kj} and h^-_{kj} and is defined as:

$$CI^i_{kj} = \frac{d(h^i_{kj}, h^c_{kj}) + d(h^i_{kj}, h^-_{kj})}{d(h^i_{kj}, h^*_{kj}) + d(h^i_{kj}, h^c_{kj}) + d(h^i_{kj}, h^-_{kj})} \quad (i \in M,\ j \in N,\ k \in T). \tag{21}$$

The improved TOPSIS-based index CI_{kj}^{i} can be employed to evaluate the performance of alternative a_i with respect to criterion c_j. By coupling the criterion weight w_j^k in terms of DM e_k, the comprehensive TOPSIS-based index $CI(a_i)$ of the characteristics for alternative a_i is expressed as follows:

$$\begin{aligned} CI(a_i) &= \frac{1}{t}\sum_{k=1}^{t}\sum_{j=1}^{n}\left(w_j^k CI_{kj}^{i}\right) \\ &= \frac{1}{t}\sum_{k=1}^{t}\sum_{j=1}^{n}\left(w_j^k \frac{d(h_{kj}^{i}, h_{kj}^{c}) + d(h_{kj}^{i}, h_{kj}^{-})}{d(h_{kj}^{i}, h_{kj}^{*}) + d(h_{kj}^{i}, h_{kj}^{c}) + d(h_{kj}^{i}, h_{kj}^{-})}\right). \end{aligned} \tag{22}$$

Significantly, the closer the alternatives' decision value h_{kj}^{i} is to alternatives' PID value h_{kj}^{*}, and the farther h_{kj}^{i} is from the alternatives' NID values h_{kj}^{c} and h_{kj}^{-}, the closer the $CI(a_i)$ is to 1. Thus, the comprehensive TOPSIS-based index $CI(a_i)$ can be used to rank the preference order of all alternatives. A larger $CI(a_i)$ indicates a better alternative a_i.

4. Numerical Application of the Proposed Methodoloy

This section presents the result of an empirical case study conducted on a well-known agri-food process company in China.

4.1. *Problem Description*

Agriculture plays an important role in China as China consumes a large number of agriculture products. Agri-food production significantly contributes to the consumption of resources and presents remarkable environmental impacts. Company ABC, located in East China, is one of the leading manufacturers of processed vegetable, edible vegetable oils and condiments in China. With 26 large manufacturing facilities, company ABC has paid a major contribution to the economy and growth in the food sector. Recently, China's government has paid considerable attention on sustainable development, which can push company ABC to incorporate the green concept into its management and administration. Company ABC is certified by ISO 14000 and uses the related guidelines to perform environmental duties, including encouraging its suppliers to improve their environmental practices and performance continuously. Company ABC needs to complete a supplier selection analysis. Under these circumstances, a decision committee consisting of three members, namely, the chief executive officer (e_1), the chief marketing manager (e_2) and an environmental expert (e_3), has been formed to determine the optimal supplier among four possible alternatives. Experts use the BWM to obtain the subjective weights of criteria. Moreover, they assess the performance of each potential green supplier in terms of criteria. The collected opinions of experts are expressed in linguistic terms, which will then be transformed into IFNs.

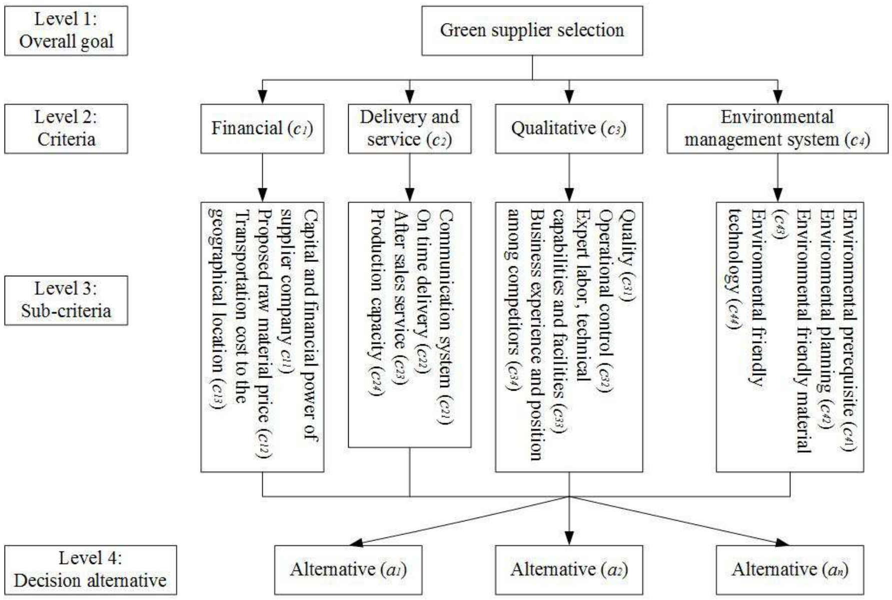

Fig. 2. Hierarchical structure for green supplier evaluation (Banaeian *et al.*, 2015).

4.2. *Evaluation Steps*

The detailed procedures for evaluating and selecting the most appropriate green supplier are shown as follows.

Step 1: Define the overall goal, criteria, sub-criteria and associated alternatives for decision-making problems, and then establish the hierarchy of the considered problem.

A conventional and green supplier evaluation standard is identified on the basis of an extensive review of green supplier evaluation literature in the agri-food industry (Banaeian *et al.*, 2018, 2015, 2014; Beske *et al.*, 2014; Borghi *et al.*, 2014; Brodt *et al.*, 2013). This standard contains four main criteria associated with 15 sub-criteria, as shown in Fig. 2.

Financial (c_1):

Capital and financial power of supplier company (c_{11}), proposed raw material price (c_{12}) and transportation cost to the geographical location (availability) (c_{13}).

Delivery and service (c_2):

Communication system (willingness to trade, attitude, acceptance of procedures and flexibility) (c_{21}), on time delivery (lead time) (c_{22}), after sales service (police, quality assurance and damage ratings) (c_{23}) and production capacity (c_{24}).

Qualitative (c_3):

Quality (suppliers' ability to access quality characteristics) (c_{31}), operational control (reporting, quality control, inventory control and research and development) (c_{32}), expert labour, technical capabilities and facilities (c_{33}) and business experience and position among competitors (c_{34}).

Table 4
Linguistic evaluation information for alternatives.

		c_{11}	c_{12}	c_{13}	c_{21}	c_{22}	c_{23}	c_{24}	c_{31}	c_{32}	c_{33}	c_{34}	c_{41}	c_{42}	c_{43}	c_{44}
e_1	a_1	FG	FG	M	M	M	G	FG	FG	M	FG	G	FG	G	FG	M
	a_2	VG	VG	FG	M	M	FG	M	M	G	M	FG	M	FG	M	FG
	a_3	VG	FG	G	FG	M	M	FG	M	M	FG	M	M	M	FG	VG
	a_4	G	G	FG	VG	FG	G	G	G	G	VG	G	VG	G	FG	G
e_2	a_1	G	M	G	G	VG	G	VG	M	G	FG	G	VG	FG	VG	G
	a_2	VG	VG	G	G	FG	FG	M	FG	FG	FG	FG	FG	FG	M	FG
	a_3	G	M	FG	M	FP	FP	M	M	FG	G	M	M	M	FG	M
	a_4	G	VG	G	G	M	G	FG	M	G	G	VG	G	FG	G	M
e_3	a_1	FG	G	VG	G	FG	FG	VG	G	FG	VG	FG	VG	FG	FG	FG
	a_2	G	VG	FG	FG	M	G	M	FG	FG	FG	FG	G	G	FG	G
	a_3	M	M	FG	M	FG	M	FG	M	G	G	FG	FG	M	M	M
	a_4	G	VG	G	M	G	FG	G	M	G	FG	VG	M	FG	M	FG

Table 5
BO and OW pairwise comparison vectors of criteria provided by DMs.

	BO pairwise comparison vector U_B^k			OW pairwise comparison vector V_W^k		
	e_1	e_2	e_3	e_1	e_2	e_3
Main criteria (c_1–c_4)	(1,3,1,5)	(2,2,1,5)	(4,5,1,3)	$(5,2,4,1)^T$	$(3,2,5,1)^T$	$(1,1,5,2)^T$
Sub-criteria (c_{11}–c_{13})	(3,5,1)	(2,6,1)	(1,5,2)	$(2,1,5)^T$	$(4,1,6)^T$	$(5,1,2)^T$
Sub-criteria (c_{21}–c_{24})	(5,1,3,3)	(5,1,2,2)	(6,2,1,4)	$(1,5,2,2)^T$	$(1,5,2,2)^T$	$(1,4,6,2)^T$
Sub-criteria (c_{31}–c_{34})	(1,4,2,2)	(1,5,2,2)	(1,5,1,2)	$(4,1,2,2)^T$	$(5,1,3,2)^T$	$(5,1,4,2)^T$
Sub-criteria (c_{41}–c_{44})	(1,2,2,5)	(1,1,2,6)	(1,2,4,5)	$(5,3,2,1)^T$	$(5,6,4,1)^T$	$(5,3,1,1)^T$

EMS (c_4):

Environmental prerequisite (environmental staff training) (c_{41}), environmental planning (program to reduce environmental impacts and green research and development) (c_{42}), environmentally friendly material (low waste: easy recycling and reuse capability) (c_{43}) and environmentally friendly technology (emission of pollutant: CO_2 equivalent and VOC, BOD and COD contents and etc.) (c_{44}).

Step 2: Design and select the evaluation scale of IFS.

In the decision process, DMs use the 9 scale linguistic terms to evaluate the performance of suppliers in terms of each criterion. Furthermore, the linguistic evaluation values are transformed into IFNs (see Table 2 for linguistic terms used for the comparative rating of suppliers). Table 4 shows the linguistic evaluation information provided by DMs.

Step 3: Determine the weight vectors of criteria and sub-criteria.

In accordance with the principle of BWM developed by Rezaei (2015, 2016), DMs initially select the best and worst criteria. Then, the DMs determine the preferences of the best criterion over all the other criteria and the preferences of the other criteria over the worst criterion by using a number from 1 to 9 (1 means equally important and 9 signifies extremely important). The BO vector U_B^k and the OW vector V_W^k provided by e_k ($k = 1, 2, 3$) are shown in Table 5.

Table 6
Weight values and CRs for the main criteria.

	e_1		e_2		e_3	
	Weights	CRs	Weights	CRs	Weights	CRs
c_1	0.418	0.087	0.254	0.097	0.133	0.087
c_2	0.150		0.203		0.111	
c_3	0.349		0.452		0.558	
c_4	0.083		0.091		0.198	

For the main criteria (c_1–c_4), the BO vector $(1, 3, 1, 5)$ and the OW vector $(5, 2, 4, 1)^T$ of e_1 are used as examples. By incorporating the elements of the vectors into Model (5), then Model (23) can be established.

$$\min \xi_1$$
$$\text{s.t.} \begin{cases} \left|\frac{w_1}{w_4} - 5\right| \leqslant \xi_1, \\ \left|\frac{w_1}{w_2} - 3\right| \leqslant \xi_1, \\ \left|\frac{w_1}{w_3} - 1\right| \leqslant \xi_1, \\ \left|\frac{w_2}{w_4} - 2\right| \leqslant \xi_1, \\ \left|\frac{w_3}{w_4} - 4\right| \leqslant \xi_1, \\ w_j \geqslant 0, \\ \sum_{j=1}^{4} w_j = 1. \end{cases} \tag{23}$$

The optimal weights $w_1^* = (0.418, 0.150, 0.349, 0.083)$ and the consistency index $\xi_1{}^* = 0.2$ can be derived by solving Model (23) with the aid of MATLAB software. Furthermore, $CR = 0.2/2.30 = 0.087 < 0.1$. Thus, the consistency level of comparisons is acceptable.

Similarly, the other results can be derived, as shown in Table 6 and Table 7.

Step 4: Determine DMs' weights with respect to different criteria.

The weight ω_1^1 of DM e_1 with respect to criterion c_{11} is used as an example.

(1) Calculate the closeness coefficient φ_1^1 of DM e_1 with respect to criterion c_{11}.

Use Eq. (7) to obtain the individual PID vector r_1^* for criterion c_{11}. In accordance with the normal distribution-based method (Xu, 2005), the associated weight vector in Eq. (7) is $\varpi = ((0.2429), 0.5142, 0.2429)$.

$$r_1^* = \left(r_{11}^*, r_{21}^*, r_{31}^*, r_{41}^*\right) = \big(\langle 0.627, 0.272, 0.101\rangle, \langle 0.779, 0.118, 0.102\rangle, \langle 0.685, 0.2, 0.115\rangle, \langle 0.7, 0.2, 0.1\rangle\big).$$

Similarly, use Eqs. (8), (9) and (10) to calculate the individual NID vectors r_1^c, r_1^{l-} and r_1^{r-} in terms of criterion c_{11}, respectively.

$$r_1^c = \left(r_{11}^c, r_{21}^c, r_{31}^c, r_{41}^c\right) = \big(\langle 0.272, 0.627, 0.101\rangle, \langle 0.118, 0.779, 0.103\rangle, \langle 0.2, 0.685, 0.115\rangle, \langle 0.2, 0.7, 0.1\rangle\big);$$

Table 7
Weight values and CRs for the sub-criteria.

	e_1		e_2		e_3		e_1	e_2	e_3
	Weights	CRs	Weights	CRs	Weights	CRs	Final weights (w_j^k)		
c_{11}	0.229	0.075	0.337	0.099	0.601	0.064	0.096	0.085	0.080
c_{12}	0.125		0.091		0.125		0.052	0.023	0.017
c_{13}	0.646		0.572		0.274		0.271	0.145	0.036
c_{21}	0.102	0.075	0.098	0.064	0.079	0.099	0.015	0.020	0.009
c_{22}	0.526		0.472		0.291		0.079	0.096	0.032
c_{23}	0.186		0.215		0.496		0.028	0.044	0.055
c_{24}	0.186		0.215		0.134		0.028	0.044	0.015
c_{31}	0.444	0.076	0.452	0.097	0.397	0.084	0.155	0.204	0.221
c_{32}	0.112		0.091		0.083		0.039	0.041	0.046
c_{33}	0.222		0.254		0.339		0.078	0.115	0.189
c_{34}	0.222		0.203		0.181		0.078	0.092	0.101
c_{41}	0.452	0.097	0.315	0.099	0.501	0.087	0.038	0.029	0.100
c_{42}	0.254		0.392		0.279		0.021	0.036	0.056
c_{43}	0.203		0.231		0.119		0.017	0.021	0.024
c_{44}	0.091		0.062		0.101		0.008	0.006	0.020

$$\begin{aligned} r_1^{l-} &= \left(r_{11}^{l-}, r_{21}^{l-}, r_{31}^{l-}, r_{41}^{l-}\right) \\ &= \left(\langle 0.6, 0.3, 0.1\rangle, \langle 0.7, 0.2, 0.1\rangle, \langle 0.45, 0.4, 0.15\rangle, \langle 0.7, 0.2, 0.1\rangle\right); \\ r_1^{r-} &= \left(r_{11}^{r-}, r_{21}^{r-}, r_{31}^{r-}, r_{41}^{r-}\right) \\ &= \left(\langle 0.7, 0.2, 0.1\rangle, \langle 0.8, 0.1, 0.1\rangle, \langle 0.8, 0.1, 0.1\rangle, \langle 0.7, 0.2, 0.1\rangle\right). \end{aligned}$$

Use Eq. (3) to calculate the distances $d(r_1^1, r_1^*)$, $d(r_1^1, r_1^c)$, $d(r_1^1, r_1^{l-})$ and $d(r_1^1, r_1^{r-})$. Furthermore, use Eq. (11) to calculate the extended closeness coefficient φ_1^1 of DM e_1 with respect to criterion c_{11}.

$$\begin{aligned} \varphi_j^k &= \frac{d(r_1^1, r_1^c) + d(r_1^1, r_1^{l-}) + d(r_1^1, r_1^{r-})}{d(r_1^1, r_1^*) + d(r_1^1, r_1^c) + d(r_1^1, r_1^{l-}) + d(r_1^1, r_1^{r-})} \\ &= \frac{0.541 + 0.171 + 0.050}{0.057 + 0.541 + 0.171 + 0.050} = 0.931. \end{aligned}$$

(2) Calculate the proximity degree η_1^1 of DM e_1 with respect to criterion c_{11}.

Use Eqs. (2) and (12) to calculate the proximity degrees γ_{i1}^{l1} $(i = 1, 2, 3, 4, l = 2, 3, 4)$. $\gamma_{11}^{21} = 0.9$, $\gamma_{21}^{21} = 1$, $\gamma_{31}^{21} = 0.9$ and $\gamma_{41}^{21} = 1$; $\gamma_{11}^{31} = 1$, $\gamma_{21}^{31} = 0.9$, $\gamma_{31}^{31} = 0.672$ and $\gamma_{41}^{31} = 1$.

Furthermore, use Eq. (13) to calculate the average proximity degree η_1^1.

$$\eta_1^1 = \frac{1}{4 \times 2} \sum_{l=1,\, l \neq k}^{3} \sum_{i=1}^{4} \gamma_{ij}^{lk} = \frac{0.9 + 1 + 0.9 + 1 + 1 + 0.9 + 0.672 + 1}{8} = 0.922.$$

Table 8
Closeness coefficients, proximity degrees and criterion weights of DMs.

	φ_j^k			η_j^k			λ_j^k ($\theta = 0.5$)			ω_j^k		
	e_1	e_2	e_3	e_1	e_2	e_3	e_1	e_2	e_3	e_1	e_2	e_3
c_{11}	0.931	0.949	0.840	0.922	0.921	0.893	0.926	0.935	0.866	0.340	0.343	0.317
c_{12}	0.912	0.908	0.931	0.913	0.926	0.930	0.913	0.917	0.931	0.331	0.332	0.337
c_{13}	0.826	0.940	0.922	0.868	0.909	0.909	0.847	0.924	0.915	0.315	0.344	0.341
c_{21}	0.836	0.922	0.846	0.811	0.873	0.856	0.823	0.897	0.851	0.320	0.349	0.331
c_{22}	0.841	0.838	0.878	0.870	0.820	0.859	0.855	0.829	0.869	0.335	0.325	0.340
c_{23}	0.958	0.929	0.877	0.952	0.941	0.914	0.955	0.935	0.896	0.343	0.335	0.322
c_{24}	0.865	0.895	0.958	0.921	0.917	0.946	0.893	0.906	0.952	0.325	0.329	0.346
c_{31}	0.828	0.842	0.890	0.881	0.910	0.914	0.854	0.876	0.902	0.325	0.332	0.343
c_{32}	0.849	0.921	0.921	0.885	0.917	0.917	0.867	0.919	0.919	0.320	0.340	0.340
c_{33}	0.882	0.943	0.884	0.879	0.921	0.883	0.881	0.932	0.884	0.327	0.345	0.328
c_{34}	0.923	0.962	0.899	0.946	0.958	0.929	0.934	0.960	0.914	0.333	0.341	0.326
c_{41}	0.857	0.964	0.853	0.835	0.888	0.831	0.846	0.926	0.842	0.324	0.354	0.322
c_{42}	0.898	0.940	0.914	0.938	0.963	0.950	0.918	0.951	0.932	0.328	0.340	0.332
c_{43}	0.925	0.876	0.822	0.913	0.876	0.864	0.919	0.876	0.843	0.348	0.332	0.320
c_{44}	0.838	0.857	0.896	0.819	0.860	0.876	0.828	0.858	0.886	0.322	0.334	0.344

(3) Derive the weight ω_1^1 of DM e_1 with respect to criterion c_{11}.

Use Eq. (14) to calculate the unified weight of DM e_1 on c_{11}, with the controlling parameter $\theta = 0.5$. The unified weight is $\lambda_1^1 = 0.926$. Similarly, $\lambda_1^2 = 0.935$ and $\lambda_1^3 = 0.866$. Then, use Eq. (15) to normalize the unified weights, that is, $\omega_1^1 = 0.340$, $\omega_1^2 = 0.343$ and $\omega_1^3 = 0.317$.

Analogously, the other results can be calculated, as shown in Table 8.

Step 5: Rank all the alternatives and select the optimal one (s).

In the following, the target is to rank all the alternatives on the basis of the improved TOPSIS method.

(1) Obtain the group decision matrix with respect to criteria.

Use Eq. (16) to calculate the weighted individual decision matrices $\hat{R}^k = (\hat{r}_{ij}^k)_{4\times 15}$ ($k = 1, 2, 3$). Then, use Eq. (17) to transform them into $H^i = (h_{kj}^i)_{3\times 15}$ ($i = 1, 2, 3, 4$), as shown in Table 9 and Table 10. The hesitancy function π is not presented because of the limited layout.

(2) Determine the alternatives' PID vector h_j^*, and NID vectors h_j^c and h_j^- on criterion c_j.

The alternatives' PID vector $h_1^* = (h_{11}^*, h_{21}^*, \dots, h_{31}^*)$ and NID vectors $h_1^c = (h_{11}^c, h_{21}^c, \dots, h_{31}^c)$ and $h_1^- = (h_{11}^-, h_{21}^-, \dots, h_{31}^-)$ on criterion c_{11} are used as an example.

Use Eqs. (18), (19) and (20) to derive the alternatives' PID and NID vectors, respectively.

$$\begin{aligned} h_1^* &= \left(h_{11}^*, h_{21}^*, \dots, h_{31}^*\right) \\ &= \left(\langle 0.4210.458, 0.121\rangle, \langle 0.424, 0.454, 0.122\rangle, \langle 0.318, 0.600, 0.082\rangle\right); \end{aligned}$$

Table 9
Weighted decision information (H^1 and H^2).

	a_1						a_2					
	e_1		e_2		e_3		e_1		e_2		e_3	
	μ	ν	μ	ν	μ	ν	μ	ν	μ	ν	μ	ν
c_{11}	0.267	0.664	0.338	0.576	0.252	0.682	0.421	0.458	0.424	0.454	0.318	0.600
c_{12}	0.261	0.672	0.180	0.738	0.334	0.581	0.413	0.467	0.414	0.465	0.419	0.460
c_{13}	0.172	0.749	0.339	0.575	0.422	0.456	0.251	0.684	0.339	0.575	0.268	0.664
c_{21}	0.174	0.746	0.343	0.570	0.329	0.587	0.174	0.746	0.343	0.570	0.262	0.671
c_{22}	0.182	0.736	0.407	0.474	0.268	0.664	0.182	0.736	0.257	0.676	0.184	0.732
c_{23}	0.338	0.576	0.332	0.583	0.255	0.679	0.270	0.662	0.265	0.668	0.321	0.596
c_{24}	0.257	0.677	0.411	0.468	0.427	0.451	0.176	0.743	0.179	0.740	0.187	0.728
c_{31}	0.257	0.677	0.180	0.737	0.338	0.576	0.176	0.743	0.263	0.670	0.269	0.662
c_{32}	0.174	0.746	0.336	0.579	0.268	0.664	0.320	0.597	0.268	0.664	0.268	0.664
c_{33}	0.259	0.675	0.271	0.660	0.410	0.470	0.177	0.741	0.271	0.660	0.259	0.674
c_{34}	0.330	0.585	0.337	0.577	0.258	0.676	0.263	0.670	0.269	0.663	0.258	0.676
c_{41}	0.257	0.677	0.435	0.442	0.405	0.476	0.176	0.743	0.277	0.653	0.321	0.595
c_{42}	0.326	0.590	0.267	0.664	0.263	0.670	0.259	0.674	0.267	0.664	0.330	0.585
c_{43}	0.273	0.657	0.414	0.466	0.254	0.681	0.188	0.727	0.180	0.738	0.254	0.681
c_{44}	0.175	0.745	0.331	0.585	0.271	0.661	0.255	0.679	0.263	0.669	0.339	0.574

Table 10
Weighted decision information (H^3 and H^4).

	a_3						a_4					
	e_1		e_2		e_3		e_1		e_2		e_3	
	μ	ν	μ	ν	μ	ν	μ	ν	μ	ν	μ	ν
c_{11}	0.421	0.458	0.338	0.576	0.173	0.748	0.336	0.579	0.338	0.576	0.318	0.600
c_{12}	0.261	0.672	0.180	0.738	0.183	0.734	0.328	0.587	0.414	0.465	0.419	0.460
c_{13}	0.316	0.602	0.270	0.661	0.268	0.664	0.251	0.684	0.339	0.575	0.336	0.578
c_{21}	0.254	0.680	0.188	0.726	0.180	0.738	0.403	0.479	0.343	0.570	0.180	0.738
c_{22}	0.182	0.736	0.153	0.798	0.268	0.664	0.264	0.668	0.176	0.743	0.336	0.578
c_{23}	0.185	0.730	0.158	0.792	0.175	0.745	0.338	0.576	0.332	0.583	0.255	0.679
c_{24}	0.257	0.677	0.179	0.740	0.272	0.659	0.323	0.593	0.260	0.673	0.341	0.573
c_{31}	0.176	0.743	0.180	0.737	0.185	0.731	0.323	0.593	0.180	0.737	0.185	0.731
c_{32}	0.174	0.746	0.268	0.664	0.336	0.579	0.320	0.597	0.336	0.579	0.336	0.579
c_{33}	0.259	0.675	0.340	0.573	0.326	0.590	0.409	0.471	0.340	0.573	0.259	0.674
c_{34}	0.180	0.737	0.185	0.731	0.258	0.676	0.330	0.585	0.423	0.455	0.408	0.473
c_{41}	0.176	0.743	0.191	0.723	0.256	0.679	0.406	0.475	0.347	0.565	0.175	0.744
c_{42}	0.178	0.741	0.184	0.733	0.180	0.737	0.326	0.590	0.267	0.664	0.263	0.670
c_{43}	0.273	0.657	0.262	0.670	0.174	0.746	0.273	0.657	0.330	0.586	0.174	0.746
c_{44}	0.404	0.476	0.181	0.737	0.186	0.729	0.321	0.596	0.181	0.737	0.271	0.661

$$\begin{aligned} h_1^c &= \left(h_{11}^c, h_{21}^c, \dots, h_{31}^c\right) \\ &= \left(\langle 0.458, 0.421, 0.121\rangle, \langle 0.454, 0.424, 0.122\rangle, \langle 0.600, 0.318, 0.082\rangle\right); \\ h_1^- &= \left(h_{11}^-, h_{21}^-, \dots, h_{31}^-\right) \\ &= \left(\langle 0.267, 0.664, 0.068\rangle, \langle 0.338, 0.576, 0.086\rangle, \langle 0.173, 0.748, 0.080\rangle\right). \end{aligned}$$

(3) Calculate the TOPSIS-based index CI_{kj}^{i} and comprehensive TOPSIS-based index $CI(a_i)$.

Use Eq. (2) to calculate the distances $d(h_{11}^{1}, h_{11}^{*})$, $d(h_{11}^{1}, h_{11}^{c})$ and $d(h_{11}^{1}, h_{11}^{-})$. Furthermore, use Eq. (21) to obtain the TOPSIS-based index CI_{11}^{1}.

$$CI_{11}^{1} = \frac{d(h_{11}^{1}, h_{11}^{c}) + d(h_{11}^{1}, h_{11}^{-})}{d(h_{11}^{1}, h_{11}^{*}) + d(h_{11}^{1}, h_{11}^{c}) + d(h_{11}^{1}, h_{11}^{-})} = \frac{0.222 + 0}{0.186 + 0.222 + 0} = 0.544.$$

Similarly, the other TOPSIS-based indices can be obtained. Then, use Eq. (22) associated with the obtained final weights in Table 7 to derive the comprehensive TOPSIS-based indices $CI(a_i)$ $(i = 1, 2, 3, 4)$.

$$CI(a_1) = 0.849, \qquad CI(a_2) = 0.814, \qquad CI(a_3) = 0.755 \quad \text{and} \quad CI(a_4) = 0.848.$$

Descend the comprehensive TOPSIS-based indices. And the ranking of all the alternatives is $a_1 \succ a_4 \succ a_2 \succ a_3$, where a_1 is the best one.

5. Results and Discussion

This section presents the analysis of the influence of varying θ on the performances of alternatives. Moreover, a comparison analysis is conducted between the proposed approach and the existing methods.

5.1. *Sensitivity Analysis*

In the existing methods (Yue, 2014), only the closeness coefficient is applied to obtain the DMs' weights or criterion weights, which is insufficient in a prudent group decision-making (GDM) process (Wan *et al.*, 2015). Table 8 shows that the closeness coefficients of DMs e_1 and e_2 in terms of criterion c_{12} are 0.912 and 0.908, respectively. The closeness coefficient of e_1 is larger than that of e_2. However, the proximity degree of DM e_1 (0.913) is smaller than that of e_2 (0.926). Similar results occur in DMs e_2 and e_3 with respect to c_{13}, DMs e_1 and e_3 with respect to c_{22}, and so on. Thus, a large closeness coefficient may not guarantee a large proximity degree. In this study, the closeness coefficient and the proximity degree are considered simultaneously, and a comprehensive measurement is developed with a control parameter θ, which can balance the effectiveness of the duplex measurements. The result of the effect of the measurements on the final performances of alternatives is shown in Table 11 and Fig. 3. When $0 \leqslant \theta \leqslant 0.2$, the comprehensive TOPSIS-based index $CI(a_4)$ is the largest, and alternative a_4 is optimal. When $0.3 \leqslant \theta \leqslant 1$, alternative a_1 becomes the best one. Although the influence is slight in the ranking result, cautiously considering the factors in a complex GDM process is necessary to select an appropriate green supplier. Generally, it is suggested to set $\theta = 0.5$, which is simple and can balance the closeness coefficient and proximity degree.

Table 11
Comprehensive TOPSIS-based indices with different θ.

θ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
$CI(a_1)$	0.8483	0.8484	0.8485	0.8486	0.8487	0.8488	0.8489	0.8490	0.8491	0.8492	0.8493
$CI(a_2)$	0.8136	0.8136	0.8137	0.8137	0.8138	0.8139	0.8139	0.8140	0.8140	0.8141	0.8141
$CI(a_3)$	0.7555	0.7554	0.7553	0.7552	0.7550	0.7549	0.7548	0.7547	0.7545	0.7544	0.7542
$CI(a_4)$	0.8488	0.8487	0.8486	0.8485	0.8484	0.8484	0.8483	0.8482	0.8481	0.8480	0.8479

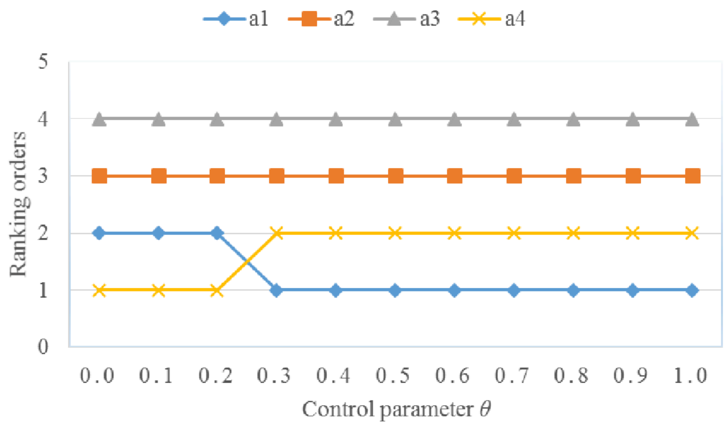

Fig. 3. Ranking orders of alternatives with varying θ.

Table 12
Results with different methods.

	IF-TOPSIS method		IF-VIKOR method				Proposed approach	
	CC_i	Ranking result	S_i	R_i	Q_i	Ranking result	CI(a_i)	Ranking result
a_1	0.688	2	0.225	0.087	0.079	$\{a_1, a_2\}$	0.849	1
a_2	0.408	3	0.581	0.144	0.583		0.814	3
a_3	0.138	4	0.859	0.193	1		0.755	4
a_4	0.755	1	0.248	0.067	0.018		0.848	2

Furthermore, this study inherits the idea of Yue (2014), and only calculates the different weights between DMs, instead of those with respect to different criteria. The other steps remain the same as this study. The outcome shows that the ranking is $a_1 \succ a_4 \succ a_2 \succ a_3$, when $\theta = 0.5$. The ranking results are always $a_1 \succ a_4 \succ a_2 \succ a_3$ even if the control parameter θ uses different values. In this way, the weights of a DM with respect to different criteria are the same, and the familiarity degree of the DM in terms of different criteria is not seriously considered. In real life, DMs may be skilled in some specific fields. Thus, allowing for the difference of DMs' weights with respect to different criteria is reasonable.

5.2. *Comparative Analysis*

The proposed approach is compared with two other distance-based methods, namely, the integrated AHP and IF-TOPSIS method (Buyukozkan and Guleryuz, 2016) and the integrated Delphi and IF-VIKOR method (Roostaee *et al.*, 2012), to verify its feasibility and validity. Some foundational and conceptual differences are observed among these methods. The integrated AHP and IF-TOPSIS method (Buyukozkan and Guleryuz, 2016) uses the AHP and has to conduct $(n^2 - n)/2$ pairwise comparisons to obtain the criterion weights. Meanwhile, the integrated Delphi and IF-VIKOR method (Roostaee *et al.*, 2012) uses the Delphi to calculate the criterion weights and may have to conduct several rounds of questionnaire to achieve a stable result. However, the proposed method employs the BWM and only requires to conduct $(2n - 3)$ comparisons. The statistical result shows that the BWM can require less comparison data but achieves more consistent and stable results (Rezaei, 2016). As for the ranking process, TOPSIS considers a majority rule, and VIKOR focuses on the smallest deviations and considers potential side effects (Opricovic and Tzeng, 2004; Shen and Wang, 2018; Wang *et al.*, 2018). The proposed method incorporates multiple NIDs into the core structure of TOPSIS. Logically, a NID can avoid a risk, and the process will further become cautious (Yue, 2014). Thus, the result yielded by the proposed approach will be more robust and cautious than those yielded by the other MCGDM methods.

Furthermore, the three methods are used to solve the same green supplier selection problem. Firstly, assume that the parameter $\theta = 0.5$ and employ the DMs' weights and criterion weights yielded by the proposed method. Then, the IF-TOPSIS (Buyukozkan and Guleryuz, 2016) and IF-VIKOR (Roostaee *et al.*, 2012) methods are used to obtain the ranking of all alternatives. The result is shown in Table 12. The best alternative yielded by the IF-TOPSIS method (Buyukozkan and Guleryuz, 2016) is a_4, and a compromise solution set yielded by the IF-VIKOR method (Roostaee *et al.*, 2012) is $\{a_1, a_4\}$. A slight difference is observed in the outcomes among the three methods. This difference may be caused by the different principles of information fusion of these methods. Figure 4 presents a visual radar diagram on the basis of the outcomes yielded in Step 5 to show the performances of alternatives with respect to criteria. Alternative a_1 exhibits saliency in criteria c_{31} and c_{33}, followed by a_4. Meanwhile, Table 7 shows that the final weights of criteria c_{31} and c_{33} are significantly larger than those of the other major criteria. Therefore, the comprehensive indices of alternatives a_1 and a_4 are larger and the two alternatives are ranked higher than the others. Along with the variation of parameter θ, the optimal alternative is within the set $\{a_1, a_4\}$. It is enough to aid an agri-food firm select an appropriate green supplier. Therefore, the proposed method is feasible and effective in solving green supplier selection problems to some degree.

6. Conclusions

The green supplier selection problem is one of the most significant issues in green supply chain management. Particularly, in China's agri-food industry, green practices play an

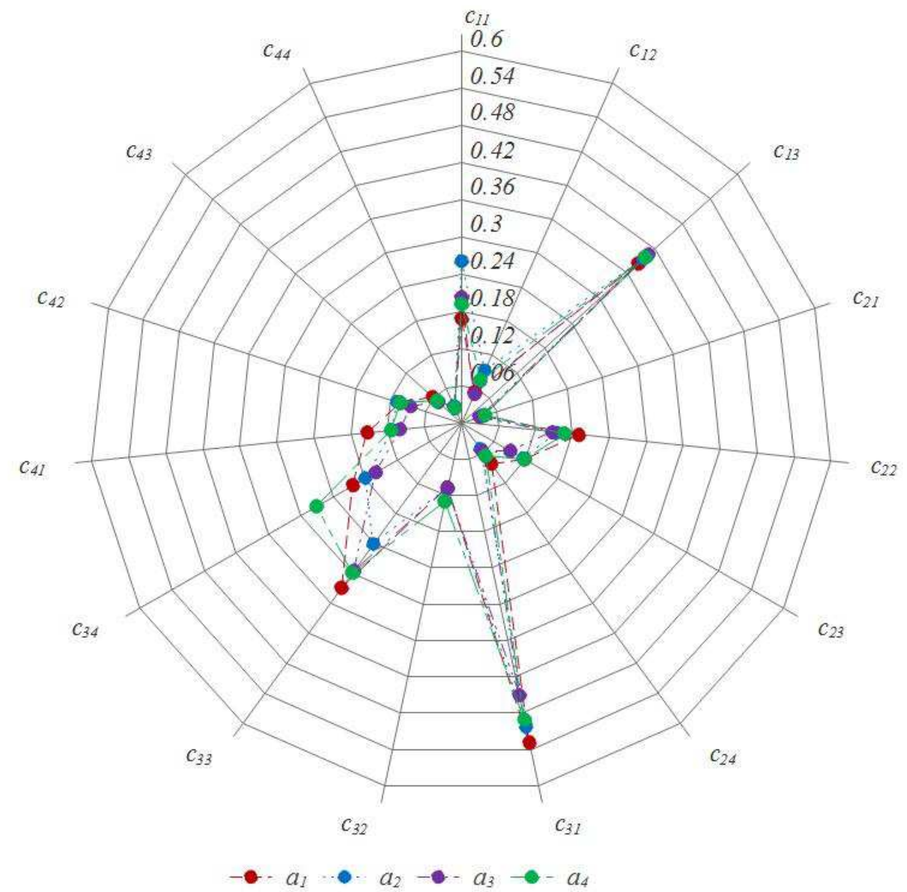

Fig. 4. Performances of alternatives with respect to criteria.

important role in leading the society towards green economy. This work develops a novel MCGDM method for solving green supplier selection problems. The proposed MCGDM model contributes to the evaluation and selection of green suppliers. This study provides the following conclusions.

(1) A new way to derive criterion weights by using BWM, which requires less comparison data, but leads to more consistent comparisons than traditional AHP, is presented.
(2) The familiarity of DMs with respect to different criteria is considered, and an improved TOPSIS structure integrated with a proximity measure is provided to calculate the DMs' weights in terms of criteria. Moreover, a comprehensive TOPSIS-based index is utilized to describe the performances of alternatives cautiously.
(3) The developed methodology is applied to address the green supplier selection problem in the agri-food industry. The sensitivity and comparative analyses demonstrate the priority and effectiveness of the proposed method.

However, some limitations are present in this study. The calculation process of the proposed approach is more complex than that of the traditional fuzzy method, such as simple arithmetic average, IF-TOPSIS and IF-VIKOR. Moreover, the consensus reaching process is not considered in the proposed MCGDM. In the future, the proposed method can be further improved by designing effective algorithms to reduce the complexity and overcome the limitation of rank reversal (Aouadni *et al.*, 2017). The consensus reaching process (Cabrerizo *et al.*, 2015; Dong *et al.*, 2016) is necessary to yield satisfactory results in MCGDM. Moreover, the BWM and TOPSIS methods are worth incorporating into other qualitative GDM situations (Cabrerizo *et al.*, 2017, 2013; Nie *et al.*, 2017). This study can also be extended to manage other similar evaluation and selection problems, in which the number of alternatives is relatively small.

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