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SUSTAINABLE FOOD SUPPLY CHAIN SCREENING AND RELATIONSHIP ANALYSIS WITH UNKNOWN CRITERIA WEIGHT INFORMATION

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Abstract. Sustainable food supply chain management (SFSC) can control food loss and waste by reducing resource consumption and environmental pollution, thereby ensuring sustainable food consumption and production patterns. Scholars have investigated specific aspects or links in SFSC but rarely studied the sustainability evaluation and selection of a whole supply chain to provide management suggestions under uncertain decision-making environments. This paper presents a comprehensive multiple criteria decision-making method called the SMAA-ORESTE method for SFSC selection. To reduce experts' efforts, the holistic acceptability index in the SMAA-2 method is used to screen inferior SFSCs from a large number of alternatives. Then, the ORESTE method is combined with the SMAA method to evaluate SFSCs under uncertain information. The ORESTE method can specifically analyze the relationship between alternatives, and the SMAA method can analyze alternatives with unknown criteria weights by Monte Carlo simulation. The proposed method ensures the robustness and credibility of obtained ranking results. An illustrative example validates the applicability and robustness of the proposed method in selecting SFSCs with unknown criteria weights.

Keywords: sustainable food supply chain, multiple criteria group decision-making, SMAA, ORESTE, food loss.

JEL Classification: D70, D81, Q01, Q18.

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1. Introduction

According to the statistics of the United Nations (United Nations, 2021), about 1.3 billion tons of waste are generated from the food supply chain every year, accounting for 22% of the total global greenhouse gas emissions. The sustainable management of the food supply chain is essential and urgent. Relevant human activities in the food sector have the greatest impact on the environment (Golini et al., 2017). About 14% of the world's food is lost in the supply chain before reaching the retail level (United Nations, 2021). In the process of food production, a large number of resources, toxic pesticides, and chemical fertilizers may be used. In the process of food transportation, food mileage will increase and some food will be lost. In addition, in the process of food use and waste disposal, there are greenhouse gas emissions, residue combustion, landfill and food waste dumping, and various other unsustainable practices (Cardoen et al., 2015). Aiming at better managing loss and waste in the food supply chain, studies on sustainable food supply chain (SFSC) management have emerged. Sustainable supply chain management refers to the integration of environmental, social, and economic capabilities that allow organizations and related supply chains to achieve long-term sustainability performance (Batista et al., 2018). According to the review made by Kumar et al. (2022), 80% of SFSC publications have come up in the past several years, which reflects that the research on SFSC is expanding and diversifying rapidly.

Existing research topics on SFSC include evaluating the sustainability of a food supply chain, waste management, business models, and innovative technologies (Kumar et al., 2022). The sustainability management of a whole SFSC that integrates sustainable production, supply chain intermediate processes, and consumption is vital for enhancing the overall sustainability of a food supply chain. Kumar et al. (2022) pointed that the food loss and sustainability of a whole supply chain should be continuously discussed to improve the overall sustainability of a food supply chain. Sustainable decisions should consider the triple bottom line of social, economic, and environmental factors, simultaneously. Since MCDM methods can help managers evaluate the performance of a supply chain from multiple dimensions (Cinelli et al., 2020), they have been widely employed to select suppliers (Yazdani et al., 2022), prioritize risks of supply chains (Yazdani et al., 2021), and design a supply chain network (Miranda-Ackerman et al., 2017) for SFSC. Some studies (Yakovleva et al., 2012; Chauhan et al., 2020; Long et al., 2021) focused on the evaluation and selection of whole SFSCs by MCDM methods. How to use a comprehensive MCDM method to measure the sustainability of a whole food supply chain still needs to be investigated.

Determining the weights of criteria is essential for MCDM problems. Owing to market fluctuations or natural disasters and the limitations of cognitive and personalized preferences, experts may not be able to provide accurate judgments regarding criteria values or criteria weights when evaluating SFSCs. Scholars (Borcherding et al., 1991; Lahdelma & Salminen, 2001) suggested that different weights of criteria can be provided for the same problem. SWARA (Yazdani et al., 2022) and BWM (Rezaei et al., 2016; Rezaei et al., 2019) methods have been used to determine criteria weights. However, it is still a challenge to reduce the influence of the uncertainty of criteria weights on decision-making results when evaluating SFSCs. Combining with Monte Carlo simulation, the stochastic multicriteria acceptability analysis (SMAA) method provides support to solve multi-criterion group decision-making problems with incomplete criteria weights. SMAA (Lahdelma et al., 1998) uses an inverse weight space analysis to describe criteria weights that make each alternative the most preferred one. Descriptive measures, including the acceptability index, central weight vector, and confidence factor, are obtained by calculating the weight combination that can give each alternative a certain rank. To overcome the disadvantage that the classical SMAA only considers the best ranks of alternatives but ignores other ranks, Lahdelma and Salminen (2001) proposed the SMAA-2 method, which considers all ranks of alternatives from the worst to the best. Thus, this study will employ the SMAA-2 method to determine the weights of criteria in SFSC evaluation.

In practical decision-making problems, experts often face the problem of screening out candidates from a large number of alternatives since evaluating all alternatives is a heavy workload. Screening out inferior alternatives can reduce the complexity of an MCDM from a large set of alternatives to a small group of alternatives that are most likely to contain the best choice (Chen et al., 2008). In the research on supply chain management, the DEA approach (Raut et al., 2018) and fuzzy screening system (Izadikhah et al., 2020) have been used to screen out inferior alternatives. However, computing procedures of these two methods are complicated. How to develop an efficient and simple method to screen our inferior alternatives becomes a challenge. In this study, inferior alternatives are first screened out if no weight combination can make them rank high based on the holistic acceptability index in the SMAA-2 method.

The SMAA method and its variants have been widely used since they were proposed (Pelissari et al., 2020). Most existing studies on SMAA methods only rank alternatives based on comprehensive performance of alternatives, ignoring criterion-level performance of alternatives, which may affect the accuracy of ranking results (Pelissari et al., 2020). Regarding the criterion-level performance of alternatives, the ELECTRE (Roy, 1971), PROMETHEE (Brans et al., 1986) and ORESTE (Roubens, 1982), as three representative outranking-based MCDM methods, consider the performance of alternatives by analyzing the indifference, incomparability, or preference relations between alternatives under each criterion. All of these methods need to determine criteria weights or the importance ranking of criteria in advance. Lahdelma and Salminen (2002) and Greco et al. (2020) integrated the SMAA method with the ELECTRE method and PROMETHEE method, respectively, to solve decision-making problems with unknown criteria weights. Owing to the PIR (Preference, indifference, incomparability) relationship analysis, the ORESTE method is found to be more reliable than the PROMETHEE and ELECTRE methods (Pastijn & Leysen, 1989; De Leeneer & Pastijn, 2002). Thus, the ORESTE method has been extended to solve different MCDM problems, such as hospital management (Zhang et al., 2018), supplier management (Liao et al., 2018), traffic management (Wang et al., 2019), shared car selection (Wu & Liao, 2018), and food supply chain evaluation (Long & Liao, 2021). However, as far as we know, no one has considered integrating the ORESTE method with the SMAA method to handle decision-making problems with unknown criteria weights by PIR relationship analysis. Since SMAA can effectively simulate PIR relationship distributions in the decision-making process to improve the flexibility and robustness of ORESTE, the SMAA-ORESTE method can adapt to complex and uncertain decision-making environments. Thus, combining the SMAA and ORESTE methods to analyze the PIR relationships between alternatives from criterion-level in the case of unknown weight information is worth studying.

Based on the above analysis, we integrate the PIR relationship analysis in ORESTE into the SMAA method, which not only overcomes the loss of information caused by the original SMAA method that ranks alternatives without considering criterion-level performance, but also overcomes the strong requirement of the traditional ORESTE method regarding complete criteria weights. The proposed method is applied to select SFSCs with a large number of alternatives. Groups of criteria weights are randomly generated from the feasible weight space for alternatives screening and relationship analysis. The SMAA-2 method is used to screen out inferior alternatives, and then the proposed SMAA-ORESTE method is employed to analyze the PIR relations between remaining alternatives. The innovative work of this study is highlighted as follows:

(1) We propose a novel method to handle uncertain criteria weights. We employ the Monte Carlo simulation to randomly generate groups of criteria weights first, and then each group of criteria weights is used for SFSC screening and PIR relationship analysis. The simulation of multiple groups of criteria weights can handle the unknown criteria weights and improve the robustness of decision-making method in MCDM problems.

(2) We utilize the holistic acceptability index in the SMAA-2 method to screen out inferior alternatives when the number of alternative SFSCs is large. The screening method can screen out inferior alternatives effectively, thereby reducing the computational complexity and the cognitive efforts of experts, as well as helping decision-makers make flexible decisions in the SFSCs evaluation process.

(3) We integrate the ORESTE method with the SMAA method to explore the PIR relations between remaining SFSCs. The SMAA-ORESTE method can calculate the probability distribution of PIR relations between any two alternatives. This allows for a clear understanding of the rank relationship of SFSCs and select suitable SFSCs when criteria weights are unknown.

The reminder of this paper is organized as follows. Section 1 reviews MCDM methods used in SFSC management, and then introduces the SMAA-2 method and ORESTE method. Section 2 introduces the proposed SMAA-ORESTE model in detail for SFSC evaluation. Section 3 provides an illustrative example. Implications are given in Section 4. Concluding remarks and discussions are pointed out in the last section.

2. Literature review

This section first reviews the literature about MCDM methods used in SFSC management. Then, Section 2.2. describes the SMAA-2 method and Section 2.3. reviews the ORESTE method. Abbreviations and notations used in this paper are explained in Appendix A and Appendix B, respectively.

2.1. Review of MCDM methods used in SFSC management

The evaluation and selection of SFSC can be regarded as an MCDM problem that involves many criteria. Patidar et al. (2021) found that "statistical analysis" and "multiple criteria decision-making technology" are the most commonly used technologies for food supply chain management. In this section, we briefly review MCDM methods applied in SFSC management.

As can be seen from Table 1, MCDM methods have been widely applied to supplier selection (Yazdani et al., 2022), risk prioritization (Yazdani et al., 2021), and supply network design (Miranda-Ackerman et al., 2017) in SFSC management. Regarding SFSC management, studies mostly focused on one specific aspect of an SFSC. For example, Validi et al. (2014) used a GA-based multi-objective approach and the TOPSIS method to manage the downstream food distribution system from producers to customers. Gupta and Shankar (2016) used an interval 2-tuple linguistic TOPSIS method to prioritize the frauds and rank the collusive behavior in the Indian Agro-Supply Chain under incomplete and uncertain information. Yazdani et al. (2022) estimated supplier selection criteria weights using a combined version of SWARA and level-based weight assessment (LBWA) in conjunction with D-numbers. Then, the MARCOS-D method was applied to obtain a ranking pre-order of different tier suppliers. Some scholars focused on the evaluation and selection of a whole SFSC, since it is vital to improve the overall sustainability of an SFSC and reduce food loss (Kumar et al., 2022). Yakovleva et al.

Table 1. Relevant MCDM methods used in SFSC management

No.	Reference	Used techniques	Determination of criteria weights	Application
1	Oglethorpe (2010)	Goal-programming approach	Directly given	Supply chain strategy selection
2	Yakovleva et al. (2012)	AHP	AHP	Supply chain evaluation
3	Validi et al. (2014)	A GA-based multi-objective approach, TOPSIS	AHP	Distribution system
4	Azadnia et al. (2015)	An integrated multi-objective approach	FAHP	Supplier selection
5	Gupta & Shankar (2016)	TOPSIS	Directly given	Ranking of collusive behavior
6	Rezaei et al. (2016)	BWM	BWM	Supplier selection
7	Govindan et al. (2017)	PROMETHEE, Simos procedure	Simos	Prioritization of green suppliers
8	Miranda-Ackerman et al. (2017)	LCA, Multi-objective optimization, GA, TOPSIS	–	Supply chain network design
9	Allaoui et al. (2018)	Two-stage hybrid multi-objective approach, AHP, OWA	AHP	Supply chain design
10	Rezaei et al. (2019)	BWM	BWM	Selection of a sustainable product-package design
11	Sufiyan et al. (2019)	fuzzy DEMATEL, ANP	ANP	Evaluate the performance of SFSCs
12	Giallanza & Puma (2020)	ELECTRE III, multi-objective programming model	Directly given	Green vehicle routing problem
13	Chauhan et al. (2020)	ANP, DEMATEL, ISM	ANP	Supply chain selection
14	Yazdani et al. (2021)	SWARA, FMEA, EDAS	SWARA	Supply chain risk management
15	Long et al. (2021)	SPAN, ORESTE	Directly given	Supply chain selection
16	Yazdani et al. (2022)	SWARA, MARCOS, LBWA	SWARA and LBWA	Supplier selection
17	Mohseni et al. (2022)	TOPSIS-AHP, AHP, and COPRAS-AHP	AHP	Identified drivers and barriers in SFSC management

(2012) used a multi-stage procedure to evaluate the sustainability performance of SFSCs based on the AHP method. Sufiyan et al. (2019) employed the fuzzy DEMATEL to corroborate interrelationships among identified performance criteria and their associated criteria in SFSC evaluation, and utilized ANP to rank alternatives. Chauhan et al. (2020) combined DEMATEL with the ISM method to identify influencing factors in maintaining an efficient supply chain for agri-produce, and employed ANP to select the best supply chain of agri-produce. Long et al. (2021) used the delegate mechanism of SPAN to determine the weights of experts and employed the ORESTE method to select an SFSC under the q-rung orthopair fuzzy environment. Mohseni et al. (2022) identified six drivers and seven barriers with the help of experts' opinions in the SFSC field, and applied ranking methods including TOPSIS-AHP, AHP, and COPRAS-AHP as well as Borda rule and Copeland method to fuse criteria ratings.

Some studies supposed that criteria weights were given directly (Oglethorpe, 2010; Gupta & Shankar, 2016; Giallanza & Puma, 2020), whereas others used methods such as the ANP (Chauhan et al., 2020), SWARA (Yazdani et al., 2022) and BWM (Rezaei et al., 2016; Rezaei et al., 2019) to determine criteria weights. However, existing research on SFSC evaluation and selection rarely took into account unknown criteria weights in the decision-making process. Due to the complexity of an SFSC and the cognitive limitations of evaluation experts, experts may only express their preference for criteria but cannot provide the accurate values of criteria weights. Besides, different decision-makers may have different views, and their views may change at different stages of SFSC management. In this regard, criteria weights may be uncertain and neglecting the uncertain characteristic of criteria weights may cause bias in decision-making results. Thus, it is necessary to consider uncertain criteria weights when developing MCDM methods to evaluate SFSCs.

2.2. The SMAA method

The SMAA method, proposed by Lahdelma et al. (1998), is an MCDM technique that does not require DMs to give their preferences on criteria weights. In SMAA, the absent information is represented in the form of probability distributions. SMAA applies an inverse weight space analysis to describe criteria weights that assign the highest rank to each alternative. Alternatives can be compared by descriptive measures such as the acceptability index, central weight vector, and confidence factor. The original SMAA method only considered the highest rank but ignored other ranks of alternatives, which makes it difficult to identify compromise alternatives.

To tackle this limitation, Lahdelma and Salminen (2001) proposed the SMAA-2 method, which inherits the advantages of the original SMAA method in dealing with incomplete information of criteria weights and assessment values of alternatives but improves the disadvantage that the original SMAA ignores other ranking information of alternatives. The SMAA-2 method analyses the sets of weight vectors of criteria for every rank of each alternative from the best to the worst, which addresses the issue of lacking knowledge and increases the credibility of ranking results.

Inferior alternatives can be screened out if no weight combination can make them rank highly. Screening out inferior alternatives can reduce the complexity of an MCDM from a large set of alternatives to a small group of alternatives that are most likely to contain the best choice (Chen et al., 2008). Raut et al. (2018) used the DEA approach to screen the maximally efficient third-party logistics providers before further evaluation. Izadikhah et al. (2020) used a fuzzy screening system to identify and remove unqualified sustainable suppliers before clustering suppliers. However, as far as we know, no scholar has introduced the alternative screening process into the SFSC management when they face a large number of alternatives. In this sense, we adopt the SMAA-2 method to screen alternatives.

Consider a general MCDM problem with m alternatives evaluated with respect to n criteria. The weight of criterion c_j is denoted as w_j, where $i = 1, 2, ..., m$, $j = 1, 2, ..., n$. The utilities of alternatives can be expressed by the combination of the alternative assessment value vector $\mathbf{g}_i = (g_{i1}, ..., g_{in})$ and the criterion weight vector $\mathbf{w} = (w_1, ..., w_n)^T$ in the feasible weight space $\mathbf{W} = \{\mathbf{w} \in R^n : w_j \geq 0 \wedge \sum_{j=1}^{n} w_j = 1\}$. The incomplete and uncertain alternative assessment values $g_{ij}(i = 1, 2, ..., m, j = 1, 2, ..., n)$ are represented by stochastic variables $\xi_i(i = 1, 2, ..., m)$ with a joint density function $f(\xi)$ in the space x. Similarly, the unknown criteria weights $w_j(j = 1, 2, ..., n)$ are replaced by a weight distribution with a joint density function $f(w)$ in the feasible weight space $\mathbf{W}$. The utility of alternative a_i is denoted as $u(\xi_i, \mathbf{w})$. The rank of each alternative can be computed as an integer by Eq. (1), where $\rho(true) = 1$ and $\rho(false) = 0$.

$$rank(\xi_i, \mathbf{w}) = 1 + \sum_{k=1}^{m} \rho(u(\xi_k, \mathbf{w}) > u(\xi_i, \mathbf{w})). \tag{1}$$

The favorable rank weight $W_i^r(\xi)$ can be defined as $W_i^r(\xi) = \{\mathbf{w} \in W : rank(\xi_i, \mathbf{w}) = r\}$, which means that $\forall\ \mathbf{w} \in W_i^r(\xi)$, alternative a_i obtains the rank r. The *rank acceptability index* b_i^r measures the variety of different valuations that grant a specific alternative rank r, calculated by Eq. (2). The *k best ranks* (*kbr*) *acceptability* a_i^k measures the variety of different valuations that assign alternative a_i any of the k best ranks. When a_i^k is close to or equal to zero, the alternative a_i will be considered as an inefficient alternative and can be eliminated. The *central kbr weight vector* $\mathbf{w}_i^k$ is defined as the expected centre of gravity of the k best ranks for alternative a_i, and calculated by Eq. (4). $\mathbf{w}_i^k$ describes a typical preference structure that would make an alternative the most preferred one when no preference is provided by decision makers. All integrals are computed by the Monte Carlo simulation.

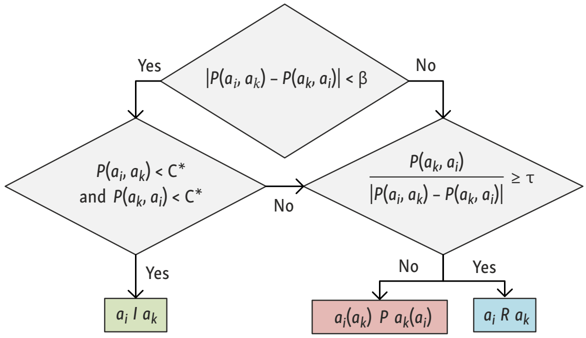
$$b_i^r = \int_X f(\xi) \int_{W_i^r(\xi)} f(\mathbf{w}) d\mathbf{w} d\xi; \tag{2}$$

$$a_i^k = \sum_{r=1}^{k} b_i^r; \tag{3}$$

$$\mathbf{w}_i^k = \frac{1}{a_i^k} \int_X f(\xi) \sum_{r=1}^{k} \int_{W_i^r(\xi)} f(\mathbf{w}) \mathbf{w} d\mathbf{w} d\xi. \tag{4}$$

2.3. The ORESTE method

The ORESTE method proposed by Roubens (1982) is an efficient MCDM method. The unique advantage of the ORESTE method is that the indifference, preference, and incomparability relations between alternatives can be analyzed in detail. It has been applied to solve practical problems, including waste management (Delhaye et al., 1991), investment decisions (Van Huylenbroeck, 1995), hospital management (Zhang et al., 2018), supplier management (Liao



Note: in Figure 1, *I* refers to the "indifference" relation; *R* refers to the "incomparability" relation; *P* refers to the "preference" relation.

Figure 1. The PIR sensitivity test (adapted from Van Huylenbroeck, 1995)

et al., 2018), traffic management (Wang et al., 2019), and select shared cars (Wu & Liao, 2018). Long and Liao (2021) applied the ORESTE to SFSC selection under the q-rung orthopair fuzzy environment when criteria weights were known. The ORESTE method has not been extended to evaluate alternatives when criteria weights are unknown.

The ORESTE method includes the following steps (Van Huylenbroeck, 1995): 1) determine the weights of criteria and the performance values of alternatives under each criterion; 2) use a preference function to calculate the preference score $P(a_i, a_k)$ of alternative a_i to alternative a_k; 3) set up the PIR structure according to the rules in Figure 1. Parameters such as the indifference threshold β, preference threshold C^* and incomparability threshold τ are set according to the practical problem. For details of the ORESTE method, please refer to Roubens (1982).

3. Methodology

For an MCDM problem with n criteria and m alternatives, the evaluation information of alternatives under various criteria is shown as a matrix $D_A = \left(g_{ij}\right)_{m\times n}$, where g_{ij} is the evaluation value of alternative a_i on criterion c_j. Without loss of generality, the weight vector of criteria $\mathbf{w} = (w_1, \ldots, w_n)^T$, joint density function $f(w_j)$, feasible weight space W, stochastic variables $\xi_i (i = 1, 2, \ldots, m)$, joint density function $f(\xi_i)$, and feasible space $X \in R^{m\times n}$ are defined as before. In this paper, we use the commonly-used linear preference function (Van Huylenbroeck, 1995) to transform the difference of evaluation scores into a preference score between 0 and 1, so as to identify the dominant relationship between alternatives. The preference indicator $P(a_i, a_k)$ of a_i over a_k is defined by Eqs (5) and (6), where q is an indifference threshold, and p is a preference threshold. $P(a_i, a_k)$ measures the degree of a_i dominant a_k.

$$P(a_i, a_k) = \frac{1}{n}\sum_{j=1}^{n} \omega_j \hat{e}_j(a_i, a_k); \tag{5}$$

$$\hat{e}_j(a_i,a_k)=\begin{cases}0, & \text{if } g_{ij}-g_{kj}\le q\\ \dfrac{\left|g_{ij}-g_{kj}\right|}{p}, & \text{if } q<g_{ij}-g_{kj}\le p.\\ 1, & \text{if } g_{ij}-g_{kj}>p\end{cases} \tag{6}$$

3.1. Alternatives screened by the SMAA-2 method

There are three indicators that can be used to evaluate and eliminate inferior alternatives, including alternatives' rank acceptability b_i^r defined by Eq. (2), the *kbr* acceptability a_i^k defined by Eq. (3), and the holistic acceptability η_i^h expressed as $\eta_i^h=\sum_{r=1}^{m}\alpha^r b_i^r$, where α^r is the weight of rank acceptability b_i^r corresponding to alternative a_i. The three common forms of rank acceptability weights are linear weights, inverse weights, and centroid weights (Lahdelma & Salminen, 2001). Here we use the form of inverse weight, that is, $\alpha^r=1/r$. The *kbr* holistic acceptability index η_i^k ($k\le m$) is defined as Eq. (7). Different from the holistic acceptability, the *kbr* holistic acceptability index is equivalent to combining the idea of the *kbr* acceptability and the holistic acceptability. This reduces the workload of calculation and is sufficient to screen out inferior alternatives. θ is the threshold for screening inferior alternatives. When $\eta_i^k<\theta$, alternative a_i will be considered as an inefficient one and can be eliminated. The values of k and θ depend on the preference of decision makers. It can be seen that the higher the acceptability of the alternative is at the top, the greater the value of η_i^k is, and then the less likely it is to be screened out, which is in line with the actual situation. Different from a_i^k, considering that the top-ranked alternative should be paid more attention to, we assign the largest weight to the first rank acceptability index and the smallest weight to the last rank acceptability index.

$$\eta_i^k=\sum_{r=1}^{k}\frac{1}{r}b_i^r. \tag{7}$$

Example 1. For three alternatives, a_1, a_2, and a_3, by the SMAA-2 method, we get the acceptability indexes of the three alternatives from the first to the third (see Table 2). As can be seen from Table 3, η_i^k almost maintains the same ranking order as a_i^k but has a better discriminating power when two alternatives have the same acceptability. For example, when r = 2, $a_1^2=a_2^2$, but it is obvious that alternative a_1 is different from alternative a_2. Therefore, this paper will use η_i^k to identify whether an alternative should be screened out.

Table 2. The acceptability indexes of three alternatives

	r = 1	r = 2	r = 3
a_1	0.5	0.3	0.2
a_2	0.2	0.6	0.2
a_3	0.3	0.1	0.6

Table 3. The comparison of results of a_i^k and η_i^k

	a_i^1	η_i^1	a_i^2	η_i^2	a_i^3	η_i^3
a_1	0.5	0.5	0.8	0.65	1	0.72
a_2	0.2	0.2	0.8	0.5	1	0.57
a_3	0.3	0.3	0.4	0.35	1	0.55

3.2. Alternatives comparison by the SMAA-ORESTE method

After inferior solutions are being screened out, the remaining alternatives need to be further compared. To do this, the weight space when two alternatives are preferent, indifferent and incomparable should be defined first.

3.2.1. The indifference relation

According to the rules of PIR sensitivity test (see Figure 1), the weight vector of the indifference relation between alternatives a_i and a_k is

$$W^I(\xi_{ik}) = \{\mathbf{w} \in W : a_i \; I \; a_k \Leftrightarrow \left|P(a_i, a_k) - P(a_k, a_i)\right| < \beta \text{ and } P(a_i, a_k) < C^* \text{ and } P(a_k, a_i) < C^*\}.$$

When alternatives a_i and a_k are indifferent, the acceptability index b_{ik}^I can be defined as Eq. (8). The central weight vector $\mathbf{w}_{ik}^I$ is defined as Eq. (9). Through calculating the central weight vector, we can know what kind of preference would lead to which actions.

$$b_{ik}^I = \int_X f(\xi) \int_{W_{ik}^I(\xi)} f(\mathbf{w}) d\mathbf{w} d\xi; \quad (8)$$

$$\mathbf{w}_{ik}^I = \frac{1}{b_{ik}^I} \int_X f(\xi) \int_{W_k^I(\xi)} f(\mathbf{w}) \mathbf{w} d\mathbf{w} d\xi. \quad (9)$$

3.2.2. The incomparability relation

The weight vector of the incomparability relation between alternatives a_i and a_k is

$$W^R(\xi_{ik}) = \{\mathbf{w} \in W : a_i \; R \; a_k \Leftrightarrow ((\left|P(a_i, a_k) - P(a_k, a_i)\right| > \beta \wedge \max(P(a_i, a_k), P(a_k, a_i)) \geq C^*) \vee \left|P(a_i, a_k) - P(a_k, a_i)\right| \leq \beta) \wedge \frac{P(a_k, a_i)}{\left|P(a_i, a_k) - P(a_k, a_i)\right|} \geq \tau\}.$$

When alternatives a_i and a_k are incomparable, the acceptability index b_{ik}^P can be defined as Eq. (10). The central weight vector $\mathbf{w}_{ik}^P$ is defined as Eq. (11).

$$b_{ik}^R = \int_X f(\xi) \int_{W_{ik}^R(\xi)} f(\mathbf{w}) d\mathbf{w} d\xi; \quad (10)$$

$$\mathbf{w}_{ik}^R = \frac{1}{b_{ik}^R} \int_X f(\xi) \int_{W_{ik}^R(\xi)} f(\mathbf{w}) \mathbf{w} d\mathbf{w} d\xi. \quad (11)$$

3.2.3. The preference relation

The weight vector of the preference relation between alternatives a_i and a_k is

$$W^P(\xi_{ik}) = \{\mathbf{w} \in W : a_i(a_k) \; P \; a_k(a_i) \Leftrightarrow ((\left|P(a_i, a_k) - P(a_k, a_i)\right| > \beta \wedge \max(P(a_i, a_k), P(a_k, a_i)) \geq C^*) \vee \left|P(a_i, a_k) - P(a_k, a_i)\right| \leq \beta) \wedge \frac{P(a_k, a_i)}{\left|P(a_i, a_k) - P(a_k, a_i)\right|} < \tau\}.$$

When alternative a_i prefers to a_k, the acceptability index b_{ik}^P can be defined as Eq. (12). The central weight vector $\mathbf{w}_{ik}^P$ can be defined as Eq. (13). The multi-dimensional integral in the SMAA method cannot be calculated by analytical method, but can be realized by Monte Carlo simulation. The Monte Carlo algorithm of the proposed method is given in Appendix C.

$$b_{ik}^P = \int_X f(\xi) \int_{W_{ik}^P(\xi)} f(\mathbf{w}) d\mathbf{w} d\xi; \tag{12}$$

$$\mathbf{w}_{ik}^P = \frac{1}{b_{ik}^P} \int_X f(\xi) \int_{W_{ik}^P(\xi)} f(\mathbf{w}) \mathbf{w} d\mathbf{w} d\xi. \tag{13}$$

3.3. The procedure of the proposed method

For ease of understanding, the procedure of the proposed method is depicted in Figure 2 and the steps are explained as follows:

Step 1. Determine relevant criteria involved in the SFSC evaluation. Experts from relevant industries are invited to evaluate the performance of SFSC alternatives under each criterion.

Step 2. The SMAA-2 method performed by the Monte Carlo algorithm is used to screen out inferior alternatives that can hardly be ranked at the top in any case. The largest round of iterations is set as ψ_1.

2(a). Randomly generate a set of criteria weights.

2(b). Calculate the utility value of each alternative based on the generated criteria weights by $u = \sum_{j=1}^{n} w_j g_{ij}$, and then rank alternatives by Eq. (1) according to the utility values of alternatives.

2(c). Check whether the maximal iteration has been reached. If yes, then go to step 2(d); otherwise, go to step (2a).

2(d). Calculate the acceptability indices of alternatives according to the record data.

2(e). Calculate the *kbr* holistic acceptability index η_i^k of each alternative. The smaller the value of η_i^k is, the easier the alternative is to be screened out.

Step 3. For the remaining alternatives, the proposed SMAA-ORESTE method is performed by the Monte Carlo algorithm. The largest round of iterations is set as ψ_1.

3(a). Generate a set of criteria weights.

3(b). Use Eq. (5) to calculate the preference intensity between any two alternatives.

3(c). Based on the preference scores between alternatives, the PIR test in the ORESTE method is used to identify the relationship between alternatives.

3(d). Check whether the maximal iteration has been reached. If yes, then go to step 3(e); otherwise, go to step (3a).

3(e). Count the number of times that two alternatives meet the indifference, incomparability, and preference relations and extract the corresponding weight vector.

3(f). Calculate the acceptability index and central weight vector of indifference, incomparability and preference relations between any two alternatives.

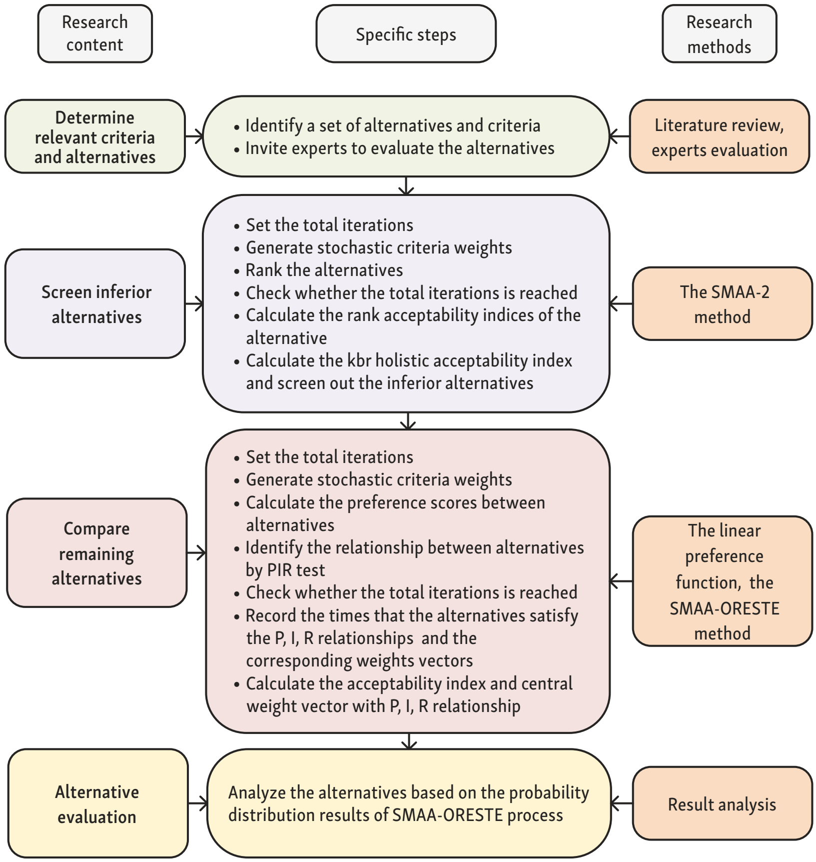


Figure 2. The frame diagram

Step 4. According to the obtained probability distributions, alternatives are divided into three categories: alternatives with high probability, alternatives with low probability, and alternatives with no obvious preference for a specific indifference, incompatibility, or preference relations. The first category of alternatives can be directly selected, the second category of alternatives can be screened out, and the third category of alternatives can be used as an alternative to the first type when the number of alternatives to be selected exceeds the total number of alternatives of the first type.

4. An illustrative example about sustainable food supplier evaluation and selection

This section uses an illustrative example regarding multi-criteria evaluation and selection of SFSCs to verify the practicability of the proposed SMAA-ORESTE method.

4.1. Criteria for SFSC evaluation

The indicator system is the foundation of SFSC evaluation and selection. Yakovleva et al. (2012) considered the criteria involved in SFSC evaluation from the stages of agriculture, food processing, food wholesale, food retail, and food catering, ignoring technology and innovation aspects. Technology and innovation are beneficial to the storage of food and the transmission of information flow, which is necessary for sustainable development. Chauhan et al. (2020) provided criteria for SFSC selection without considering the criteria at the social level, which is an important aspect of SFSC assessment. Long et al. (2021) mentioned that sustainability in SFSC selection should be considered, including environmental and social indicators, but did not give specific sub-criteria. Direct assessment and measurement of sustainability are abstract and difficult. Providing a comprehensive index system for SFSC evaluation and selection covering the supply chain links from production to retail is necessary, which can avoid missing important indicators. The indicators for SFSC evaluation can be selected based on the triple bottom line principle, taking into account the indicators at the economic, environmental, and social levels. Next, we sort out factors involved in various links of agricultural food before sales, including production and packaging, transportation and logistics path planning, storage methods and infrastructure construction. Figure 3 shows the whole supply chain from suppliers to end consumers, including forward supply chain and reverse supply chain. Criteria related to economic, environmental and social aspects involved in each link of an SFSC are explored. It is noteworthy that we primarily present a comprehensive framework of criteria for evaluating SFSCs in a general context. When applied to specific practical issues, such as the evaluation of fresh food supply chains, one can refer to several key aspects proposed in this paper to establish more tailored sub-criteria that align with different supply chain evaluation concerns.

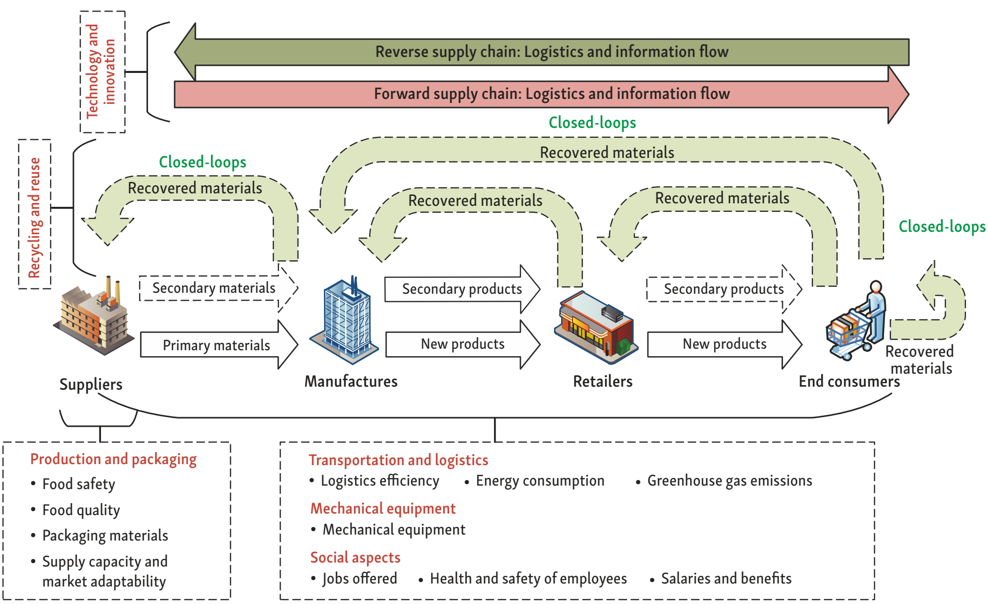


Figure 3. The framework of an SFSC (adapted from Batista et al., 2018 and Long et al., 2023)

(1) Production and packaging

Food safety, quality, economy, environmental protection and applicability of packaging materials involved in the production process need to be considered. In addition, it is also necessary to consider the supplier's supply capacity and market adaptability.

- Safety (c_1): Food safety refers to that food is non-toxic and harmless, meeting the nutritional requirements without causing harm to human health.
- Quality (c_2): Objectively, quality refers to the inherent physical characteristics of products. Subjectively, quality refers to the perceived quality of consumers. Providing products with different quality according to the needs of consumers can improve the competitiveness of food producers (Grunert, 2005).
- Packaging materials (c_3): The packaging system should take into account the product quality, shelf life, ergonomics, environmental protection and sustainability (Azzi et al., 2012).
- Supply capacity and market adaptability (c_4): Productivity and production flexibility are also important. Whether a supplier's supply capacity can meet the market demand, whether it has a certain safety reserve capacity, and whether it can make timely adjustments with respect to the market demand need to be considered. Maintaining the balance between supply and demand is usually based on demand forecasting (Chauhan et al., 2018).

(2) Transportation and logistics

The transportation mode selection among suppliers, dealers and retailers should be considered in the transportation process, which involves logistics efficiency, energy consumption, greenhouse gas emissions.

- Logistics efficiency (c_5): Logistics efficiency is closely related to the overall construction of a logistics system, and a logistics system should meet the requirements of customers at a certain service level (Manzini & Accorsi, 2013). The logistics efficiency in a food supply chain directly affects the quality and taste of food (Li et al., 2014).
- Energy consumption (c_6): Energy consumption refers to the energy consumed in production and life. There is a lot of energy consumption in the production and transportation of a supply chain. It is important to choose an appropriate transportation mode and make a good route planning to control energy consumption.
- Greenhouse gas emissions (c_7): 75–90% of greenhouse gas emissions come from the upstream of a supply chain (Tidy et al., 2016). With urgent environmental concerns and the implementation of a low-carbon policy, controlling the emission of greenhouse gases in food production and transportation contributes to the environment and society.

(3) Mechanical equipment

- Mechanical equipment (c_8): The allocation of machinery and equipment in production, transportation and storage is one of the factors to evaluate the ability of a supply chain, especially for a food supply chain. Most foods have high requirements for storage mode and temperature.

(4) Social aspects

The social aspects mainly refer to the responsibility to the government, society, employees, customers and business partners (Pullman et al., 2009).

- Jobs offered (c_9): The more jobs provided by the whole supply chain are, the greater contribution it will make in improving the social employment rate.
- Health and safety of employees (c_{10}): The safety of working environment and the reasonable arrangement of working time and intensity are necessary for the safety and health of employees (Giannakis & Papadopoulos, 2016).
- Salaries and benefits (c_{11}): Workers should be paid appropriate salary and other due treatment according to relevant laws and regulations of the industry (Giannakis & Papadopoulos, 2016).

(5) Technology and innovation

- IT systems (c_{12}): The infrastructure allocation of information technology, the allocation of relevant technical experts and the integration of information systems are conducive to ensuring the transmission and sharing of information flow. They can also meet the growing needs of consumers for food traceability. For example, the food traceability system can form a reliable and continuous information flow in a supply chain, monitor the production process and flow direction of food, and be used to identify problems and implement recalls (Zhong et al., 2017).

(6) Recycling and reuse

- Recycling and reuse (c_{13}): Due to the wrong prediction of market demand, climate conditions, poor packaging and storage, poor handling and transportation and other problems, the food supply chain will produce lots of losses and waste. Recycling and proper waste management are necessary to support sustainable development. Khan et al. (2022) found that the closed-loop supply chain strategy is the most suitable strategy for a food supply chain to achieve sustainable development, which involves product recycling and reverse logistics.

4.2. Model application

Step 1. The criteria for SFSC evaluation are determined in Section 4.1. As an illustrative example, we set the performance values of 25 alternatives given by experts under 13 criteria as shown in Table 4. The performance value of each alternative under each criterion is determined using the value ranging from 0 to 100 (without loss of generality, we suppose that the higher the score of an alternative under each criterion is, the better the performance of the alternative is). Note that the data in Table 4 is just used to demonstrate the calculation process of our proposed method.

Step 2. We use the SMAA-2 method to screen out inferior alternatives that are hardly ranked at the top in any case. First, randomly generate a set of criteria weights. Then, calculate the utility value of each alternative according to the generated criteria weights using the additive value function $u = \sum_{j=1}^{n} w_j g_{ij}$ and rank alternatives according to the utility value by Eq. (1).

Table 4. Evaluation values of 25 alternatives under 13 criteria

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}
a_1	90	89	77	88	82	80	86	89	78	87	88	87	86
a_2	63	60	60	66	68	65	67	65	68	62	60	64	67
a_3	82	70	84	73	75	87	76	88	89	71	84	86	70
a_4	44	27	51	15	20	18	20	43	33	38	48	35	59
a_5	63	86	46	28	29	49	41	55	19	38	84	33	84
a_6	34	31	53	29	55	43	57	34	45	55	51	45	43
a_7	92	92	94	45	56	70	62	94	85	83	100	88	80
a_8	84	96	97	81	93	99	90	60	94	86	89	42	50
a_9	54	57	49	33	58	33	45	43	31	50	30	57	43
a_{10}	60	66	67	64	70	64	69	64	70	70	65	63	60
a_{11}	93	84	82	89	99	83	90	96	54	67	60	81	98
a_{12}	91	78	80	89	79	56	53	98	63	97	98	84	99
a_{13}	89	94	82	81	93	85	96	84	94	94	93	83	95
a_{14}	85	92	48	81	100	54	63	86	82	84	95	81	58
a_{15}	30	58	65	46	46	42	74	21	41	74	36	29	39
a_{16}	55	68	60	53	69	69	41	54	43	52	62	52	42
a_{17}	50	33	30	28	22	48	67	73	25	44	53	37	63
a_{18}	83	77	84	80	79	82	82	85	76	77	84	79	78
a_{19}	45	41	48	46	37	30	24	32	42	49	26	23	24
a_{20}	63	55	24	58	47	70	46	63	69	68	60	28	49
a_{21}	75	65	69	66	68	71	64	74	64	67	60	70	71
a_{22}	36	34	49	34	30	47	44	34	25	44	24	50	41
a_{23}	42	42	44	50	42	42	49	45	43	48	42	40	47
a_{24}	22	56	22	59	20	36	38	46	48	34	29	42	49
a_{25}	77	75	78	75	72	77	75	75	73	70	73	76	76

Repeat the above process until the maximum iterations is reached. The largest round of iterations (ψ_1) is set as 10, 000. Next, based on 10000 simulation iterations results, calculate the *kbr* holistic acceptability index η_i^k of each alternative by Eq. (7). The threshold θ for screening inferior alternatives is set as 0.09. 15 alternatives with $\eta_i^k < \theta$ were screened out, shown in Table 5.

Step 3. The proposed SMAA-ORESTE method is used to calculate the acceptability index of indifference, preference and incomparability between the remaining 11 alternatives (Alternative a_{24}, which was screened out as an inferior alternative during the screening process, is introduced to test its performance under the SMAA-ORESTE method proposed in Section 3.2). First, randomly generate a set of criteria weights. Then, we use the linear preference function to calculate the pairwise preference scores between the *remaining* 11 alternatives. The preference scores are used for PIR test. Repeat the above process until the maximum iterations is reached. The largest round of iterations (ψ_2) is set as 10, 000. Through counting the number of times that make two alternatives meet the PIR relationship and extracting the corresponding weight vector, the acceptability indices and central weight vector are obtained. The values of relevant parameters are: b = 0.1, C^* = 0.03, t = 3, q = 0, p = 100. The results are shown in Tables 6–9.

Table 5. The *kbr* holistic acceptability index η_i^k and corresponding ranking of alternatives

Alternatives	The *kbr* holistic acceptability index η_i^k (k = 25)	Rank	Is it inferior
a_1	0.44	2	
a_2	0.08	11	✓
a_3	0.15	8	
a_4	0.04	22	✓
a_5	0.06	16	✓
a_6	0.05	18	✓
a_7	0.18	6	
a_8	0.25	4	
a_9	0.05	18	✓
a_{10}	0.08	11	✓
a_{11}	0.28	3	
a_{12}	0.24	5	
a_{13}	0.99	1	
a_{14}	0.13	9	
a_{15}	0.06	16	✓
a_{16}	0.07	14	✓
a_{17}	0.05	18	✓
a_{18}	0.17	7	
a_{19}	0.04	22	✓
a_{20}	0.07	14	✓
a_{21}	0.09	10	
a_{22}	0.04	22	✓
a_{23}	0.05	18	✓
a_{24}	0.04	22	✓
a_{25}	0.08	11	✓

Table 6. The acceptability index b_{ik}^l with indifference relationship between alternatives

	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_1	0	0.1860	0.1563	0.0585	0.4085	0.3463	**0.6210**	0.0486	**0.7106**	0	0
a_3	0.1860	0	0.1347	0.0174	0.0479	0.0328	0.0182	0.0715	**1**	0.0028	0
a_7	0.1563	0.1347	0	0.0027	0.0053	0.0987	0.0136	0.0626	0.1168	0.0006	0
a_8	0.0585	0.0174	0.0027	0	0.0029	0.0005	0.0785	0.0309	0.0389	0.0001	0
a_{11}	0.4085	0.0479	0.0053	0.0029	0	0.1312	0.1153	0.0081	0.2557	0.0002	0
a_{12}	0.3463	0.0328	0.0987	0.0005	0.1312	0	0.0609	0.0744	0.1602	0.0007	0
a_{13}	0.6210	0.0182	0.0136	0.0785	0.1153	0.0609	0	0.0128	0.0377	0	0
a_{14}	0.0486	0.0715	0.0626	0.0309	0.0081	0.0744	0.0128	0	0.1590	0.0023	0
a_{18}	0.7106	1	0.1168	0.0389	0.2557	0.1602	0.0377	0.159	0	0.0008	0
a_{21}	0	0.0028	0.0006	0.0001	0.0002	0.0007	0	0.0023	0.0008	0	0
a_{24}	0	0	0	0	0	0	0	0	0	0	0

Note: significant points that are most likely to be in indifference relations are bolded.

Table 7. The acceptability index b_{ik}^{R} with incomparability relationship between alternatives

	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_1	0	0	0.0151	0.2448	0.0611	0.0228	0	0	0	0	0
a_3	0	0	**0.4540**	**0.4465**	0.2905	0.3980	0	0.3674	0	0	0
a_7	0.0151	0.4540	0	**0.4961**	0.4232	0.3542	0.0001	0.3369	**0.4472**	0.0002	0
a_8	0.2448	0.4465	0.4961	0	**0.5043**	**0.5361**	0	0.2708	**0.4710**	0.0018	0
a_{11}	0.0611	0.2905	0.4232	0.5043	0	0.3649	0	0.2224	0.2005	0	0
a_{12}	0.0228	0.3980	0.3542	0.5361	0.3649	0	0	0.1454	0.3519	0	0
a_{13}	0	0	0.0001	0	0	0	0	0	0	0	0
a_{14}	0	0.3674	0.3369	0.2708	0.2224	0.1454	0	0	0.1936	0.0041	0
a_{18}	0	0	0.4472	0.4710	0.2005	0.3519	0	0.1936	0	0	0
a_{21}	0	0	0.0002	0.0018	0	0	0	0.0041	0	0	0
a_{24}	0	0	0	0	0	0	0	0	0	0	0

Note: significant points that are most likely to be in incomparability relations are bolded.

Table 8. The acceptability index $b_{ik}^{P}(i<k)$ with preference relationship between alternatives

	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_1	0	**0.8140**	**0.8284**	**0.6534**	**0.5253**	**0.6301**	**0**	**0.9514**	0.2894	**1**	**1**
a_3	0	0	0.1556	0.0791	0.0310	0.0613	**0**	0.4740	0	**0.9972**	**1**
a_7	0	0	0	0.1409	0.0912	0.0857	**0**	**0.5037**	0.1778	**0.9992**	**1**
a_8	0	0	0	0	0.1737	0.2154	**0**	**0.643**	0.3676	**0.9981**	**1**
a_{11}	0	0	0	0	0	0.3284	**0**	**0.7474**	**0.5213**	**0.9998**	**1**
a_{12}	0	0	0	0	0	0	**0**	**0.7673**	0.4048	**0.9993**	**1**
a_{13}	0	0	0	0	0	0	0	**0.9872**	**0.9623**	**1**	**1**
a_{14}	0	0	0	0	0	0	0	0	0.0374	**0.9936**	**1**
a_{18}	0	0	0	0	0	0	0	0	0	**0.9992**	**1**
a_{21}	0	0	0	0	0	0	0	0	0	0	**1**
a_{24}	0	0	0	0	0	0	0	0	0	0	0

Note: significant points that are most likely to be in preference relations are bolded.

Table 9. The acceptability index $b_{ik}^{P}(i>k)$ with preference relationship between alternatives

	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_1	0	0	0	0	0	0	0	0	0	0	0
a_3	0	0	0	0	0	0	0	0	0	0	0
a_7	0.0002	0.2557	0	0	0	0	0	0	0	0	0
a_8	0.0433	0.4570	0.3603	0	0	0	0	0	0	0	0
a_{11}	0.0051	**0.6306**	**0.4803**	0.3191	0	0	0	0	0	0	0
a_{12}	0.0008	**0.5079**	0.4614	0.2480	0.1755	0	0	0	0	0	0
a_{13}	**0.3790**	**0.9818**	**0.9863**	**0.9215**	**0.8847**	**0.9391**	0	0	0	0	0
a_{14}	0	0.0871	0.0968	0.0553	0.0221	0.0129	**0**	0	0	0	0
a_{18}	0	0	0.2582	0.1225	0.0225	0.0831	**0**	**0.6100**	0	0	0
a_{21}	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	0	0
a_{24}	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	0

Note: significant points that are most likely to be in preference relations are bolded.

Step 4. According to the obtained probability distributions in Table 6–9, we can analyze the relationship between alternatives. The acceptability index matrix of the indifference relationship in Table 6 and the incomparability relationship in Table 7 are symmetrical. The acceptability index matrix of preference relationship between alternatives in Tables 8 and 9 are not symmetrical.

From Tables 8 and 9, we can see that alternative a_{21} and alternative a_{24} performed poorly and other alternatives outperformed them. Therefore, these two alternatives can be eliminated.

Alternative a_1 is superior to other alternatives except alternative a_{13} and alternative a_{18} with a probability of more than 50%. Alternative a_{13} is superior to other alternatives with a probability of approaching or exceeding 90% except alternative a_1. It shows that, among these alternatives, alternative a_1 and alternative a_{13} are relatively better. Furtherly, alternative a_{13} is superior to alternative a_1 with a probability of 37.9%, and alternative a_1 cannot be superior to alternative a_{13}. Except for alternative a_{21} and alternative a_{24}, other alternatives are better than alternative a_{14} with a probability of greater than 50% except alternative a_3, and alternative a_{14} is hardly better than other alternatives at the same time. Therefore, alternative a_{14} is inferior to other alternatives.

From Table 6, there is no difference between alternative a_3 and alternative a_{18}. Alternative a_1 has no difference with alternative a_{13} and alternative a_{18} with a probability of 62.10% and 71.06%, respectively.

For the relationship between any two of the remaining alternatives that have not been analyzed, they do not have a particularly obvious preference for a specific relationship. Figure 4 is used to clearly display the relationships between alternatives (to show the relationship more conveniently, we omit obscure relationship data).

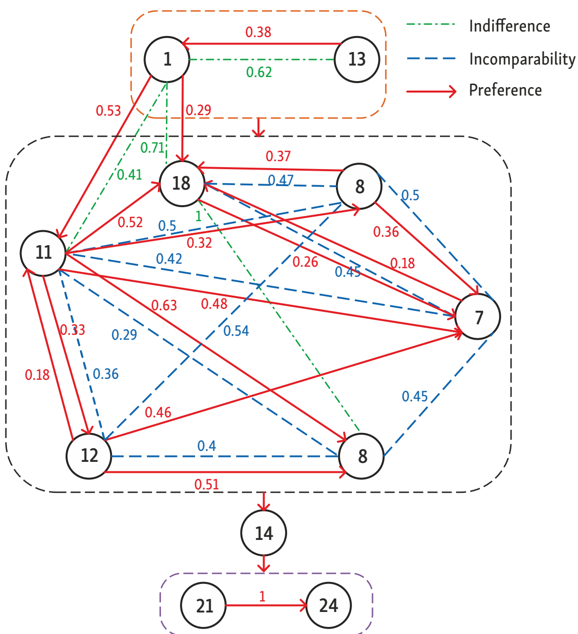


Figure 4. The relations of alternatives

We can see that the relations between alternatives in the black dotted box of Figure 4 is complex, but one obvious feature is that there are few indifference relations between those alternatives, but more preference and incomparability relations, which shows that the performance of these alternatives are inconsistent under many criteria.

Without introducing the preference of decision-makers, if only one alternative can be selected as the best alternative, we can recommend alternative a_{13}; if two alternatives can be selected, we can recommend alternative a_{13} and alternative a_1. If we need to select more than three alternatives, we will choose from the alternatives in the black dotted box in the middle. If two alternatives are compared and one needs to be selected, the one with greater preference probability is recommended. For example, compared with alternative a_{11} and alternative a_3, we recommend alternative a_{11}. Because under the condition that the two are in an incomparability relation with a probability of 29%, alternative a_{11} prefers alternative a_3 with a probability of 63%, but alternative a_3 is almost impossible to prefer alternative a_{11}.

After introducing all or part of the preferences of decision makers, the relations between alternatives will have some changes. The method proposed in this paper can be used to obtain the relationship diagram between alternatives without introducing the preferences of decision makers.

Note that by analyzing the results of the central weight vector under the three types of relations between alternatives, we find that the proposed central weight vector sometimes cannot get good results. For example, when alternative a_{13} is better than alternative a_{24} under all or almost all criteria, the 10000 groups of criteria weights generated by simulation meet the preference relations between alternatives. The central weight vector calculated based on this result shows that the weights of all criteria are equal, indicating that the central weight vector is invalid in this case. This can be used as the direction of improvement and in-depth research in the future. Moreover, we obtain 363 groups (11 x 11 x 3) of central weight vectors, which is too large for direct analysis. Therefore, we only provide the central weight vector here in order to know the significant weight vector in a specific relationship between any two alternatives.

4.3. Sensitivity analysis

To see the changes of alternatives relations under different parameters, we conduct sensitivity analysis on parameters β, C^* and τ. The results are shown in Tables A.3–A.6 in Appendix D.

From Table A.3–A.6 in Appendix D, we can see that there is little change in the relationship between alternatives under different parameter values, especially for parameters β and τ, indicating that the results are robust. It can be seen from Table A.3 that the value of C^* has a great impact on the indifference relations between alternatives. When C^* changes from 0.03 to 0.025, the probability of indifference relations between alternatives decreases significantly. This is because when the value of C^* becomes smaller, the conditions to meet the indifference relations between alternatives are more stringent. At the same time, the probabilities of other relations between alternatives increase. We highlight the values with obvious changes in grey in Tables A.3–A.6. From Tables A.4–A.6, we can observe that when τ changes from 3 to 2.5, the acceptability index b_{ik}^R with incomparability relations between alternative a_i and a_k

increases slightly while the acceptability index b_{ik}^{P} with preference relations between alternative a_i and a_k increases slightly. The reason is that, as τ decreases, the conditions for satisfying incomparability relations between alternatives are relaxed, while the conditions for satisfying preference relationship between alternatives become more stringent. This is consistent with the content presented in Figure 1 of the PIR sensitivity tests. The influence of β on the variation of the results is relatively small compared to the influence of C^* on the results, with a difference of approximately 0.01, not exceeding 0.1. The reason is that β controls the difference between the preference score of alternative a_i over alternative a_k and the preference score of alternative a_k over alternative a_i, while C^* directly controls the preference score of alternative a_i and alternative a_k. In general, the values of these parameters are determined by the decision-maker according to the specific decision-making scenario, which will not have much impact on the results. It indicates that the proposed method is robust regarding the changes of different parameters.

4.4. Comparisons with other MCDM methods

To verify the effectiveness of the proposed method, two MCDM methods, MARCOS (Stević et al., 2020) and TOPSIS (Mohseni et al., 2022) are employed to compare with the proposed method. We also use the SMAA method to determine criteria weights and the number of simulations is 10,000. The simulation results of the ranking distribution of 11 alternatives are shown in Tables A.7 and A.8 in Appendix E. Based on the results of the ranking distribution, we conclude the ranking orders of 11 alternatives according to the alternative with the highest probability under each level (bold fonts in two Tables). The ranking orders are shown in Table 10 and Figure 5.

From Table 10 and Figure 5, we can observe that the best (a_{13}) and the worst (a_{24}) alternatives are the same among the three methods, which indicates that the proposed method can effectively identify alternatives. Compared with the TOPSIS method, the proposed method has different rank orders in alternatives 11, 12, 8, 18, and 3. But the differences between the ranks of these five alternatives and those obtained by other two methods are less than 3. Compared with the MARCOS method, the proposed method has different rank orders in alternatives 18, 3, 7, 14, and 8. The differences between the ranks of these alternatives and those obtained by other two methods are 1, except for alternative 8 (9^{th} in MARCOS and 5^{th} in the proposed method). Although there are some differences of the decision-making results among the three methods since the MCDM methods have different characteristics, the ranking differences are low, indicating that the proposed method can generate robust orders of alternatives.

Compared with MARCOS and TOPSIS, the proposed method can not only give a ranking of alternatives but also help decision-makers understand the differences between alternatives. The proposed method focuses on the advantages and disadvantages between alternatives rather than relying solely on numerical comparisons, which makes it more reflective of the decision-maker's subjective preferences in decision making. Besides, the proposed method is able to process uncertainty caused by lacking decision-making information or cognitive limitations.

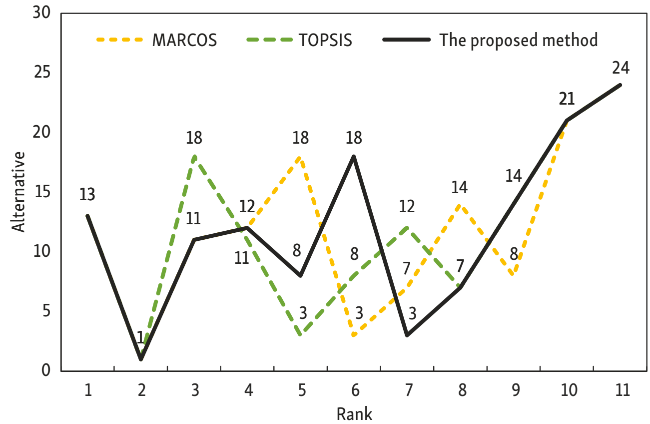


Figure 5. The ranking orders of alternatives using three methods

Table 10. Ranking orders of alternatives using different methods

Rank	MARCOS	TOPSIS	The proposed method
1	a_{13}	a_{13}	a_{13}
2	a_1	a_1	a_1
3	a_{11}	a_{18}	a_{11}
4	a_{12}	a_{11}	a_{12}
5	a_{18}	a_3	a_8
6	a_3	a_8	a_{18}
7	a_7	a_{12}	a_3
8	a_{14}	a_7	a_7
9	a_8	a_{14}	a_{14}
10	a_{21}	a_{21}	a_{21}
11	a_{24}	a_{24}	a_{24}

5. Implications

We can obtain some insights from this study. Theoretically, the proposed method can overcome some limitations of existing methods for the evaluation and selection of SFSCs. The proposed method allows for the representation of PIR relationships among alternatives in situations where criteria weights are unknown (see Figure 4). In contrast, conventional methods that directly rank alternatives fail to capture the presence of incomparability and indifference relations among alternatives. The method proposed in this paper can be used to evaluate, design, and manage the growth of a supply chain. In the context of sustainable development, it provides regulatory reference indicators and the direction of improvement for government regulators.

First, for the evaluation of SFSCs, we considered all links of the supply chain and relevant criteria. A comprehensive evaluation system is conducive to the evaluation of a supply chain. We identified the advantages of different supply chains and the growth space to be strengthened. At the same time, the performance values under different criteria cannot compensate for each other in SFSC management. For example, the high logistics efficiency and high food quality of a supply chain cannot compensate for its impact on the environment. The proposed method does not directly calculate the comprehensive values of different supply chain alternatives, but considers the performance values of all criteria simultaneously, and considers the preference, indifference, and incomparability relations between SFSCs. The proposed method not only gives the differences between alternatives, enabling managers to better understand the differences between alternatives, but also generates a ranking of alternatives to determine the best and the worst alternatives.

Second, a screening process is introduced to screen out inferior SFSCs before evaluation and selection, which takes into account the excessive number of alternative SFSCs in the actual scenario and facilitates the follow-up work. The screening process used in this paper does not need to introduce the preferences of decision-makers. Through 10,000 simulations, supply chains with a low probability of reaching the top rank are identified as inferior supply chains. This process ensures the accuracy and objectivity of the results because the screened supply chains cannot be selected under almost any criterion weight distribution. The screening process effectively reduces computational efforts and enables decision-makers to clearly understand the advantages and disadvantages of the remaining alternatives through results analysis.

Third, the proposed method can deal with the situation where criteria weights are unknown, which is rarely studied in the management of SFSCs. When criteria weights are unknown, the probability of preference, indifference, and incomparability relationships between alternative SFSCs is clearly given. The proposed method makes full use of the decision-making information and improves the reliability of decision-making results. Evaluating an SFSC requires the consideration of various criteria and demands a high level of expertise from decision-makers. It is difficult to provide accurate weights of criteria and determine the proportion of economic, environmental, and social criteria. In addition, managers may pay different attention to the criteria at different stages of SFSC management. In the start-up period, the company strives for survival and has great financial pressure. It may focus on the economy but not pay much attention to controlling the impact on the environment. After experiencing the development period and reaching the mature period, the company pays more attention to the sustainable development of the supply chain. We analyze the central weight vector when supply chains are in different relationships. Based on the relationships, the proposed model provides flexibility for the determination of criteria weights and a robust method for expressing preference uncertainty in real-world decision-making processes (e.g., preferences of criteria or preferences of alternatives).

6. Conclusions

This paper proposed a comprehensive MCDM method called the SMAA-ORESTE method to evaluate and select SFSCs. Specifically, considering that there are a large number of supply chain alternatives and criteria weights are unknown, first, the screening standard of the *kbr* holistic acceptability index in the SMAA-2 method was used to screen out inferior alternatives to reduce the cognitive efforts of decision-makers and computing complexity. Then, for the remaining alternatives, the proposed SMAA-ORESTE method was used to analyze the indifference, incomparability, and preference relations between alternatives to construct the decision-making matrix of preference relations. The SMAA-ORESTE method explicitly dealt with the incompleteness of criteria weights considering the PIR relations between alternatives through the Monte Carlo simulation. A case study of SFSC selection was provided to verify the effectiveness of the proposed method. The results of sensitivity analysis and comparisons with other MCDM methods showed that the proposed SMAA-ORESTE method was robust in evaluating SFSCs.

Although this paper addressed some problems, there are still some limitations that should be solved in the future. First, this paper only considered the cardinality data. However, experts may provide the weight and evaluation information of alternatives through other forms, such as interval numbers or linguistic terms. To avoid decision bias in the decision-making process, it is important to process the data uncertainty (not just the information of criteria weights) under different information expressions. Additionally, this paper did not consider the interactions between criteria in MCDM problems.

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APPENDIX

A. Abbreviations

Table A1. List of abbreviations

Abbreviation	Interpretation
AHP	Analytic Hierarchy Process
ANP	Analytic network process
BWM	Best-worst method
DEMATEL	Decision making trial and evaluation laboratory
EDAS	Evaluation of Data based on average Assessment methods
ELECTRE	Elimination et choix traduisant la realité in French
FMEA	Failure mode and effect analysis
GA	Genetic algorithms
ISM	Interpretive structural modeling
LCA	Life cycle assessment
ORESTE	Organisation, rangement et Synthèse de données relarionnelles, in French
OWA	Ordered weighted averaging aggregation method
PROMETHEE	Preference ranking organization method for enrichment of evaluations
SMAA	Stochastic multicriteria acceptability analysis
SPAN	Social participatory allocation network
SWARA	Step-wise Weight Assessment Ratio Analysis
TOPSIS	Technique for order performance by similarity to ideal solution
VIKOR	Vise kriterijumska optimizacija kompromisno resenje, in Serbian
MARCOS	Measurement of alternatives and ranking according to compromise solution

B. Notations

Table A2. List of symbols

Symbol	Meaning
$a_i (i = 1,2,\cdots,m)$	A set of m alternatives
$c_j (j = 1,2,\cdots,n)$	A set of n criteria
ω_j	The weight of criterion c_j
g_{ij}	The evaluation information of alternative a_i under criterion c_j
$P(a_i, a_k)$	Preference intensity of alternative a_i to alternative $a\backslash_k$
I	Indifference relationship
R	Incomparability relationship
P	Preference relationship
p	Preference threshold (When calculating preference indicators)
q	Indifference threshold (When calculating preference indicators)
$W_{ik}^I(\xi)$	The weight vector of indifference relations
b_{ik}^I	The acceptability index when $a_i\, I\, a_k$
w_{ik}^I	The central weight vector when $a_i\, I\, a_k$
p_{ik}^I	The confidence factor when $a_i\, I\, a_k$
$W_{ik}^R(\xi)$	The weight vector of incomparability relations
b_{ik}^R	The acceptability index when $a_i\, R\, a_k$
w_{ik}^R	The central weight vector when $a_i\, R\, a_k$
p_{ik}^R	The confidence factor when $a_i\, R\, a_k$
$W_{ik}^P(\xi)$	The weight vector of preference relations
b_{ik}^P	The acceptability index when $a_i\, P\, a_k$
w_{ik}^P	The central weight vector when $a_i\, P\, a_k$
p_{ik}^P	The confidence factor when $a_i\, P\, a_k$
ψ_1	Total simulation times of SMAA-2
ψ_2	Total simulation times of SMAA-ORESTE
h_{ij}^I	The number of times that alternative a_i and alternative a_k meet the condition of $a_i\, I\, a_k$
h_{ij}^R	The number of times that alternative a_i and alternative a_k meet the condition of $a_i\, R\, a_k$
h_{ij}^P	The number of times that alternative a_i and alternative a_k meet the condition of $a_i\, P\, a_k$

C. The pseudo code of the SMAA-ORESTE method

Algorithm. Computing the central weight vectors and the acceptability indices by Monte Carlo simulation.

Input: x-decision matrix, ψ_2-Maximum iterations, β, C^*, τ

Output: the central weights vectors (w_I, w_R, w_P1, w_P2) and acceptability index(b_I, b_R, b_P1, b_P2) of three relationships between any two alternatives

```
for i = 1 : m
    for j = 1 : m
        Initialize simulated numbers of three relationship among alternatives;
        Initialize weights of three relationship among alternatives;
    end
end
//main loop
for k = 1 : ψ2
    w := rand(1,n); // Generate a set of weight vector randomly
    t := fun(w,x); //Compute the preference score between alternatives
    for i = 1 : m
        for j = 1 : m
            if |t(i,j) − t(j,i)| < β then
                if t(i,j) < C* and t(j,i) < C* then
                    if i ≠ j then
                        w1(i,j) := w1(i,j) + w  // Record the weights of indifferent relationship
                        between alternative i and j.
                        h_I(i,j) := h_I(i,j) + 1; // Count the number of indifferent relationship
                    endif
                else
                    if min(t(i,j),t(j,i)) / |t(i,j) − t(j,i)| ≥ τ then
                        w2(i,j) := w2(i,j) + w;
                        h_R(i,j) := h_R(i,j) + 1;
                    else
                        if i ≤ j then
                            if t(i,j) > t(j,i) then
                                w31(i,j) := w31(i,j) + w;
                                h_P1(i,j) := h_P1(i,j) + 2;
                        else
                                w32(i,j) := w32(i,j) + w;
                                h_P2(i,j) := h_P2(i,j) + 2;
                        endif
                    endif
                endif
            endif
        elseif
```

```
                    if min(t(i,j),t(j,i)) / |t(i,j) − t(j,i)| ≥ τ then
                        w2(i,j) := w2(i,j) + w;
                        h_R(i,j) := h_R(i,j) + 1;
                    else
                        if i ≤ j then
                            if t(i,j) > t(j,i)
                                w31(i,j) := w31(i,j) + w;
                                h_P1(i,j) := h_P1(i,j) + 2;
                        else
                                w32(i,j) := w32(i,j) + w;
                                h_P2(i,j) := h_P2(i,j) + 2;
                        endif
                        endif
                endif
            endif
        endfor
    endfor
endfor
Initialize central weights vectors(w_I, w_R, w_P1, w_P2) and acceptability index(b_I,b_R,
b_P1, b_P2) of three relationships between alternatives
for i = 1:m
    for j = 1:m
        if h_I(i,j) > 0 then
            w_I(i,j) := w1(i,j) / h_I(i,j);
            b_I(i,j) := h_I(i,j) / K_W;
        end
        if h_R(i,j) > 0 then
            w_R(i,j) := w2(i,j) / h_R(i,j);
            b_R(i,j) := h_R(i,j) / K_W;
        end
        if h_P1(i,j) > 0 then
            w_P1(i,j) := w31(i,j) / h_P1(i,j);
            b_P1(i,j) := h_P1(i,j) / 2 / K_W;
        end
        if h_P2(i,j) > 0 then
            w_P2(i,j) := w32(i,j) / h_P2(i,j);
            b_P2(i,j) := h_P2(i,j) / 2 / K_W;
        endif
    end
end
```

D. The results of sensitivity analysis

Table A3. The acceptability index b_{ik}^{l} with indifference relations between alternatives with different parameters

	β	C^*	τ	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_1	0.1	0.03	3	0	0.1860	0.1563	0.0585	0.4085	0.3463	**0.6210**	0.0486	**0.7106**	0	0
	0.08	0.03	3	0	0.1843	0.1536	0.0609	0.4184	0.3367	0.6211	0.0513	0.7247	0	0
	0.1	0.025	3	0	0.0657	0.0688	0.0157	0.1980	0.1808	0.3063	0.0165	0.3630	0	0
	0.1	0.03	2.5	0	0.1926	0.1575	0.0576	0.4194	0.3438	0.6244	0.0468	0.7217	0	0
a_3	0.1	0.03	3	0.1860	0	0.1347	0.0174	0.0479	0.0328	0.0182	0.0715	1	0.0028	0
	0.08	0.03	3	0.1843	0	0.1326	0.0174	0.0477	0.0338	0.0201	0.0713	1	0.0030	0
	0.1	0.025	3	0.0657	0	0.0284	0.0030	0.0112	0.0069	0.0054	0.0192	0.9991	0.0005	0
	0.1	0.03	2.5	0.1926	0	0.1369	0.0176	0.0502	0.0320	0.0191	0.0718	1	0.0029	0
a_7	0.1	0.03	3	0.1563	0.1347	0	0.0027	0.0053	0.0987	0.0136	0.0626	0.1168	0.0006	0
	0.08	0.03	3	0.1536	0.1326	0	0.0035	0.0049	0.1042	0.0164	0.0642	0.1171	0.0010	0
	0.1	0.025	3	0.0688	0.0284	0	0.0006	0.0011	0.0275	0.0059	0.0184	0.0252	0.0004	0
	0.1	0.03	2.5	0.1575	0.1369	0	0.0024	0.0053	0.1024	0.0154	0.0671	0.1173	0.0010	0
a_8	0.1	0.03	3	0.0585	0.0174	0.0027	0	0.0029	0.0005	0.0785	0.0309	0.0389	0.0001	0
	0.08	0.03	3	0.0609	0.0174	0.0035	0	0.0027	0.0004	0.0788	0.0308	0.0378	0	0
	0.1	0.025	3	0.0157	0.0030	0.0006	0	0.0006	0	0.0384	0.0110	0.0090	0	0
	0.1	0.03	2.5	0.0576	0.0176	0.0024	0	0.0032	0.0006	0.0840	0.0305	0.0397	0	0
a_{11}	0.1	0.03	3	0.4085	0.0479	0.0053	0.0029	0	0.1312	0.1153	0.0081	0.2557	0.0002	0
	0.08	0.03	3	0.4184	0.0477	0.0049	0.0027	0	0.1305	0.1157	0.0058	0.2575	0.0004	0
	0.1	0.025	3	0.1980	0.0112	0.0011	0.0006	0	0.0532	0.0523	0.0013	0.0844	0	0
	0.1	0.03	2.5	0.4194	0.0502	0.0053	0.0032	0	0.1292	0.1205	0.0063	0.2627	0.0003	0
a_{12}	0.1	0.03	3	0.3463	0.0328	0.0987	0.0005	0.1312	0	0.0609	0.0744	0.1602	0.0007	0
	0.08	0.03	3	0.3367	0.0338	0.1042	0.0004	0.1305	0	0.0610	0.0823	0.1651	0.0003	0
	0.1	0.025	3	0.1808	0.0069	0.0275	0	0.0532	0	0.0299	0.0197	0.0491	0	0
	0.1	0.03	2.5	0.3438	0.0320	0.1024	0.0006	0.1292	0	0.0617	0.0765	0.1601	0.0003	0
a_{13}	0.1	0.03	3	0.6210	0.0182	0.0136	0.0785	0.1153	0.0609	0	0.0128	0.0377	0	0
	0.08	0.03	3	0.6211	0.0201	0.0164	0.0788	0.1157	0.0610	0	0.0120	0.0388	0	0
	0.1	0.025	3	0.3063	0.0054	0.0059	0.0384	0.0523	0.0299	0	0.0026	0.0093	0	0
	0.1	0.03	2.5	0.6244	0.0191	0.0154	0.0840	0.1205	0.0617	0	0.0134	0.0388	0	0
a_{14}	0.1	0.03	3	0.0486	0.0715	0.0626	0.0309	0.0081	0.0744	0.0128	0	0.159	0.0023	0
	0.08	0.03	3	0.0513	0.0713	0.0642	0.0308	0.0058	0.0823	0.0120	0	0.1595	0.0024	0
	0.1	0.025	3	0.0165	0.0192	0.0184	0.0110	0.0013	0.0197	0.0026	0	0.0550	0.0004	0
	0.1	0.03	2.5	0.0468	0.0718	0.0671	0.0305	0.0063	0.0765	0.0134	0	0.1579	0.0016	0

End of Table A3

	β	C^*	τ	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_{18}	0.1	0.03	3	0.7106	1	0.1168	0.0389	0.2557	0.1602	0.0377	0.1590	0	0.0008	0
	0.08	0.03	3	0.7247	1	0.1171	0.0378	0.2575	0.1651	0.0388	0.1595	0	0.0006	0
	0.1	0.025	3	0.3630	0.9991	0.0252	0.0090	0.0844	0.0491	0.0093	0.0550	0	0	0
	0.1	0.03	2.5	0.7217	1	0.1173	0.0397	0.2627	0.1601	0.0388	0.1579	0	0.0003	0
a_{21}	0.1	0.03	3	0	0.0028	0.0006	0.0001	0.0002	0.0007	0	0.0023	0.0008	0	0
	0.08	0.03	3	0	0.0030	0.0010	0	0.0004	0.0003	0	0.0024	0.0006	0	0
	0.1	0.025	3	0	0.0005	0.0004	0	0	0	0	0.0004	0	0	0
	0.1	0.03	2.5	0	0.0029	0.0010	0	0.0003	0.0003	0	0.0016	0.0003	0	0
a_{24}	0.1	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.025	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0	0

Note: significant points that are most likely to be in indifference relations are marked in green and bold.

Table A4. The acceptability index b_{ik}^{R} with incomparability relations between alternatives with different parameters

	β	C^*	τ	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_1	0.1	0.03	3	0	0	0.0151	0.2448	0.0611	0.0228	0	0	0	0	0
	0.08	0.03	3	0	0	0.0166	0.2472	0.0585	0.0216	0	0.0001	0	0	0
	0.1	0.025	3	0	0	0.0452	0.2772	0.1565	0.0816	0	0.0013	0	0	0
	0.1	0.03	2.5	0	0	0.0278	0.2974	0.0817	0.0367	0	0.0002	0	0	0
a_3	0.1	0.03	3	0	0	**0.4540**	**0.4465**	0.2905	0.3980	0	0.3674	0	0	0
	0.08	0.03	3	0	0	0.4506	0.4455	0.2991	0.4051	0	0.3671	0	0	0
	0.1	0.025	3	0	0	0.5209	0.4538	0.3176	0.4106	0	0.4059	0	0	0
	0.1	0.03	2.5	0	0	0.5093	0.5085	0.3445	0.4630	0	0.4316	0	0	0
a_7	0.1	0.03	3	0.0151	0.4540	0	**0.4961**	0.4232	0.3542	0.0001	0.3369	**0.4472**	0.0002	0
	0.08	0.03	3	0.0166	0.4506	0	0.5043	0.4233	0.3404	0.0002	0.3295	0.4465	0	0
	0.1	0.025	3	0.0452	0.5209	0	0.4956	0.4403	0.3939	0.0002	0.3589	0.5087	0	0
	0.1	0.03	2.5	0.0278	0.5093	0	0.5671	0.4872	0.3988	0.0004	0.3754	0.5074	0.0002	0
a_8	0.1	0.03	3	0.2448	0.4465	0.4961	0	**0.5043**	**0.5361**	0	0.2708	**0.4710**	0.0018	0
	0.08	0.03	3	0.2472	0.4455	0.5043	0	0.5050	0.5526	0	0.2663	0.4745	0.0017	0
	0.1	0.025	3	0.2772	0.4538	0.4956	0	0.5101	0.5408	0.0013	0.2825	0.4895	0.0019	0
	0.1	0.03	2.5	0.2974	0.5085	0.5671	0	0.5776	0.6172	0.0003	0.3094	0.5363	0.0017	0
a_{11}	0.1	0.03	3	0.0611	0.2905	0.4232	0.5043	0	0.3649	0	0.2224	0.2005	0	0
	0.08	0.03	3	0.0585	0.2991	0.4233	0.505	0	0.3586	0	0.2173	0.2035	0	0
	0.1	0.025	3	0.1565	0.3176	0.4403	0.5101	0	0.4023	0.0010	0.2298	0.2943	0	0
	0.1	0.03	2.5	0.0817	0.3445	0.4872	0.5776	0	0.4099	0	0.2643	0.2380	0	0

End of Table A4

	β	C^*	τ	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_{12}	0.1	0.03	3	0.0228	0.3980	0.3542	0.5361	0.3649	0	0	0.1454	0.3519	0	0
	0.08	0.03	3	0.0216	0.4051	0.3404	0.5526	0.3586	0	0.0002	0.1375	0.3679	0	0
	0.1	0.025	3	0.0816	0.4106	0.3939	0.5408	0.4023	0	0.0016	0.1692	0.4180	0	0
	0.1	0.03	2.5	0.0367	0.4630	0.3988	0.6172	0.4099	0	0.0006	0.1785	0.4142	0	0
a_{13}	0.1	0.03	3	0	0	0.0001	0	0	0	0	0	0	0	0
	0.08	0.03	3	0	0	0.0002	0	0	0.0002	0	0	0	0	0
	0.1	0.025	3	0	0	0.0002	0.0013	0.0010	0.0016	0	0	0	0	0
	0.1	0.03	2.5	0	0	0.0004	0.0003	0	0.0006	0	0	0	0	0
a_{14}	0.1	0.03	3	0	0.3674	0.3369	0.2708	0.2224	0.1454	0	0	0.1936	0.0041	0
	0.08	0.03	3	0.0001	0.3671	0.3295	0.2663	0.2173	0.1375	0	0	0.1865	0.0046	0
	0.1	0.025	3	0.0013	0.4059	0.3589	0.2825	0.2298	0.1692	0	0	0.2605	0.0057	0
	0.1	0.03	2.5	0.0002	0.4316	0.3754	0.3094	0.2643	0.1785	0	0	0.2376	0.0057	0
a_{18}	0.1	0.03	3	0	0	0.4472	0.4710	0.2005	0.3519	0	0.1936	0	0	0
	0.08	0.03	3	0	0	0.4465	0.4745	0.2035	0.3679	0	0.1865	0	0	0
	0.1	0.025	3	0	0	0.5087	0.4895	0.2943	0.4180	0	0.2605	0	0	0
	0.1	0.03	2.5	0	0	0.5074	0.5363	0.2380	0.4142	0	0.2376	0	0	0
a_{21}	0.1	0.03	3	0	0	0.0002	0.0018	0	0	0	0.0041	0	0	0
	0.08	0.03	3	0	0	0	0.0017	0	0	0	0.0046	0	0	0
	0.1	0.025	3	0	0	0	0.0019	0	0	0	0.0057	0	0	0
	0.1	0.03	2.5	0	0	0.0002	0.0017	0	0	0	0.0057	0	0	0
a_{24}	0.1	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.025	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0	0

Note: significant points that are most likely to be in incomparability relations are bolded.

Table A5. The acceptability index $b^P_{ik}(i < k)$ with preference relations between alternatives with different parameters

	β	C^*	τ	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_1	0.1	0.03	3	0	**0.8140**	**0.8284**	**0.6534**	**0.5253**	**0.6301**	**0**	**0.9514**	0.2894	**1**	**1**
	0.08	0.03	3	0	0.8157	0.8296	0.6508	0.5199	0.6414	0	0.9486	0.2753	1	1
	0.1	0.025	3	0	0.9343	0.8837	0.6556	0.6241	0.7312	0	0.9822	0.6370	1	1
	0.1	0.03	2.5	0	0.8074	0.8146	0.6061	0.4953	0.6185	0	0.9530	0.2783	1	1
a_3	0.1	0.03	3	0	0	0.1556	0.0791	0.0310	0.0613	**0**	0.4740	0	**0.9972**	**1**
	0.08	0.03	3	0	0	0.1586	0.0737	0.0338	0.0632	0	0.4768	0	0.9970	1
	0.1	0.025	3	0	0	0.1632	0.0770	0.0328	0.0657	0	0.4868	0	0.9995	1
	0.1	0.03	2.5	0	0	0.1267	0.0622	0.0235	0.0504	0	0.4297	0	0.9971	1

End of Table A5

	β	C^*	τ	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_7	0.1	0.03	3	0	0	0	0.1409	0.0912	0.0857	**0**	**0.5037**	0.1778	**0.9992**	**1**
	0.08	0.03	3	0	0	0	0.1358	0.0959	0.0956	0	0.5103	0.1747	0.999	1
	0.1	0.025	3	0	0	0	0.1427	0.0933	0.1041	0	0.5291	0.2022	0.9996	1
	0.1	0.03	2.5	0	0	0	0.1131	0.0768	0.0826	0	0.4764	0.1588	0.9988	1
a_8	0.1	0.03	3	0	0	0	0	0.1737	0.2154	**0**	**0.643**	0.3676	**0.9981**	**1**
	0.08	0.03	3	0	0	0	0	0.1724	0.2093	0	0.6515	0.3721	0.9983	1
	0.1	0.025	3	0	0	0	0	0.1719	0.2126	0	0.653	0.3789	0.9980	1
	0.1	0.03	2.5	0	0	0	0	0.1431	0.1786	0	0.6143	0.3289	0.9983	1
a_{11}	0.1	0.03	3	0	0	0	0	0	0.3284	**0**	**0.7474**	**0.5213**	**0.9998**	**1**
	0.08	0.03	3	0	0	0	0	0	0.3372	0	0.7536	0.5109	0.9996	1
	0.1	0.025	3	0	0	0	0	0	0.3473	0	0.7488	0.5868	1	1
	0.1	0.03	2.5	0	0	0	0	0	0.3085	0	0.7139	0.4812	0.9997	1
a_{12}	0.1	0.03	3	0	0	0	0	0	0	**0**	**0.7673**	0.4048	**0.9993**	**1**
	0.08	0.03	3	0	0	0	0	0	0	0	0.7679	0.3889	0.9997	1
	0.1	0.025	3	0	0	0	0	0	0	0	0.7945	0.4414	1	1
	0.1	0.03	2.5	0	0	0	0	0	0	0	0.7359	0.3609	0.9997	1
a_{13}	0.1	0.03	3	0	0	0	0	0	0	0	**0.9872**	**0.9623**	**1**	**1**
	0.08	0.03	3	0	0	0	0	0	0	0	0.9880	0.9612	1	1
	0.1	0.025	3	0	0	0	0	0	0	0	0.9974	0.9907	1	1
	0.1	0.03	2.5	0	0	0	0	0	0	0	0.9866	0.9612	1	1
a_{14}	0.1	0.03	3	0	0	0	0	0	0	0	0	0.0374	**0.9936**	**1**
	0.08	0.03	3	0	0	0	0	0	0	0	0	0.0330	0.9930	1
	0.1	0.025	3	0	0	0	0	0	0	0	0	0.0446	0.9939	1
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0.0251	0.9927	1
a_{18}	0.1	0.03	3	0	0	0	0	0	0	0	0	0	**0.9992**	**1**
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0.9994	1
	0.1	0.025	3	0	0	0	0	0	0	0	0	0	1	1
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0.9997	1
a_{21}	0.1	0.03	3	0	0	0	0	0	0	0	0	0	0	**1**
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0	1
	0.1	0.025	3	0	0	0	0	0	0	0	0	0	0	1
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0	1
a_{24}	0.1	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.025	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0	0

Note: significant points that are most likely to be in preference relations are marked in bolded.

Table A6. The acceptability index $b_{ik}^{P}(i > k)$ with preference relations between alternatives

	β	C^{*}	τ	a_1	a_3	a_7	a_8	a_{11}	a_{12}	a_{13}	a_{14}	a_{18}	a_{21}	a_{24}
a_1	0.1	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.025	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0	0
a_3	0.1	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.025	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0	0
a_7	0.1	0.03	3	0.0002	0.2557	0	0	0	0	0	0	0	0	0
	0.08	0.03	3	0.0002	0.2582	0	0	0	0	0	0	0	0	0
	0.1	0.025	3	0.0023	0.2875	0	0	0	0	0	0	0	0	0
	0.1	0.03	2.5	0.0001	0.2271	0	0	0	0	0	0	0	0	0
a_8	0.1	0.03	3	0.0433	0.4570	0.3603	0	0	0	0	0	0	0	0
	0.08	0.03	3	0.0411	0.4634	0.3564	0	0	0	0	0	0	0	0
	0.1	0.025	3	0.0515	0.4662	0.3611	0	0	0	0	0	0	0	0
	0.1	0.03	2.5	0.0389	0.4117	0.3174	0	0	0	0	0	0	0	0
a_{11}	0.1	0.03	3	0.0051	**0.6306**	0.4803	0.3191	0	0	0	0	0	0	0
	0.08	0.03	3	0.0032	0.6194	0.4759	0.3199	0	0	0	0	0	0	0
	0.1	0.025	3	0.0214	0.6384	0.4653	0.3174	0	0	0	0	0	0	0
	0.1	0.03	2.5	0.0036	0.5818	0.4307	0.2761	0	0	0	0	0	0	0
a_{12}	0.1	0.03	3	0.0008	**0.5079**	0.4614	0.2480	0.1755	0	0	0	0	0	0
	0.08	0.03	3	0.0003	0.4979	0.4598	0.2377	0.1737	0	0	0	0	0	0
	0.1	0.025	3	0.0064	0.5168	0.4745	0.2466	0.1972	0	0	0	0	0	0
	0.1	0.03	2.5	0.0010	0.4546	0.4162	0.2036	0.1524	0	0	0	0	0	0
a_{13}	0.1	0.03	3	**0.3790**	**0.9818**	**0.9863**	**0.9215**	**0.8847**	**0.9391**	0	0	0	0	0
	0.08	0.03	3	0.3789	0.9799	0.9834	0.9212	0.8843	0.9388	0	0	0	0	0
	0.1	0.025	3	0.6937	0.9946	0.9939	0.9603	0.9467	0.9685	0	0	0	0	0
	0.1	0.03	2.5	0.3756	0.9809	0.9842	0.9157	0.8795	0.9377	0	0	0	0	0
a_{14}	0.1	0.03	3	0	0.0871	0.0968	0.0553	0.0221	0.0129	**0**	0	0	0	0
	0.08	0.03	3	0	0.0848	0.0960	0.0514	0.0233	0.0123	0	0	0	0	0
	0.1	0.025	3	0	0.0881	0.0936	0.0535	0.0201	0.0166	0	0	0	0	0
	0.1	0.03	2.5	0	0.0669	0.0811	0.0458	0.0155	0.0091	0	0	0	0	0
a_{18}	0.1	0.03	3	0	0	0.2582	0.1225	0.0225	0.0831	**0**	**0.6100**	0	0	0
	0.08	0.03	3	0	0	0.2617	0.1156	0.0281	0.0781	0	0.6210	0	0	0
	0.1	0.025	3	0	0.0009	0.2639	0.1226	0.0345	0.0915	0	0.6399	0	0	0
	0.1	0.03	2.5	0	0	0.2165	0.0951	0.0181	0.0648	0	0.5794	0	0	0
a_{21}	0.1	0.03	3	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	0	0
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.025	3	0	0	0	0.0001	0	0	0	0	0	0	0
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0	0
a_{24}	0.1	0.03	3	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	0
	0.08	0.03	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.025	3	0	0	0	0	0	0	0	0	0	0	0
	0.1	0.03	2.5	0	0	0	0	0	0	0	0	0	0	0

Note: significant points that are most likely to be in preference relations are bolded.

E. Results of comparisons with other MCDM methods

Table A7. The probability distribution of alternatives in different ratings (MARCOS)

Alternative	1	2	3	4	5	6	7	8	9	10	11
a_1	0.0001	**0.671**	0.299	0.0294	0.0005	0	0	0	0	0	0
a_3	0	0	0.0088	0.0517	0.0969	**0.1794**	0.2947	0.2694	0.0991	0	0
a_7	0.0002	0.0228	0.0715	0.1339	0.1426	0.0968	**0.1546**	0.1983	0.1793	0	0
a_8	0.0019	0.1236	0.1551	0.1649	0.1256	0.0928	0.0862	0.1373	**0.1126**	0	0
a_{11}	0.0049	0.1147	**0.2662**	0.2849	0.1296	0.0662	0.0471	0.0531	0.0333	0	0
a_{12}	0.0026	0.058	0.1948	**0.2733**	0.1635	0.0914	0.0977	0.0976	0.0211	0	0
a_{13}	**0.9903**	0.0096	0.0001	0	0	0	0	0	0	0	0
a_{14}	0	0.0003	0.0045	0.032	0.063	0.0646	0.0901	**0.1945**	0.5507	0.0003	0
a_{18}	0	0	0	0.0299	**0.2783**	0.4088	0.2296	0.0498	0.0036	0	0
a_{21}	0	0	0	0	0	0	0	0	0.0003	**0.9997**	0
a_{24}	0	0	0	0	0	0	0	0	0	0	**1**

Table A8. The probability distribution of alternatives in different ratings (TOPSIS)

Alternative	1	2	3	4	5	6	7	8	9	10	11
a_1	0	**0.95**	0.0491	0.0009	0	0	0	0	0	0	0
a_3	0	0.0003	0.0229	0.1725	**0.3719**	0.3009	0.1084	0.022	0.0011	0	0
a_7	0	0.0015	0.0255	0.0321	0.064	0.128	0.2403	**0.2988**	0.2097	0.0001	0
a_8	0.0003	0.0262	0.1135	0.0837	0.142	**0.1901**	0.164	0.2062	0.074	0	0
a_{11}	0.0001	0.0208	0.2328	**0.183**	0.1866	0.1686	0.1061	0.0755	0.0265	0	0
a_{12}	0	0.0006	0.0788	0.077	0.1376	0.1756	**0.2904**	0.216	0.024	0	0
a_{13}	**0.9996**	0.0004	0	0	0	0	0	0	0	0	0
a_{14}	0	0.0002	0.0061	0.0078	0.0173	0.032	0.0905	0.1815	**0.6575**	0.0071	0
a_{18}	0	0	**0.4713**	0.443	0.0806	0.0048	0.0003	0	0	0	0
a_{21}	0	0	0	0	0	0	0	0	0.0072	**0.9928**	0
a_{24}	0	0	0	0	0	0	0	0	0	0	**1**