GREEN SUPPLER SELECTION BY AN INTEGRATED METHOD WITH STOCHASTIC ACCEPTABILITY ANALYSIS AND MULTIMOORA

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Abstract. In the process of supplier selection for green supply chain management, uncertain information may appear in alternatives' performances or experts' preferences. The stochastic multi-criteria acceptability analysis (SMAA) is a beneficial technique to tackling the uncertain information in such a problem and the MULTIMOORA is a robust technique to aggregate alternatives' utilities. This study dedicates to proposing an SMAA-MULTIMOORA method by considering the advantages of both methods. The integrated method can accept uncertain information as inputs. The steps of the SMAA-MULTIMOORA are illustrated. A case study about the selection of green suppliers is given to show the validity and robustness of the SMAA-MULTIMOORA method.

Keywords: green supplier selection, stochastic information, multi-criteria acceptability analysis, SMAA, MULTIMOORA.

JEL Classification: C44, D70, D81, L83.

Introduction

More and more attention all over the world have been paid to the Green Supply Chain Management (GSCM) due to the increasingly serious problems on resources and environment (Tseng et al., 2019). A green supply chain and a traditional supply chain is different as the former not only considers the optimization and coordination of the supply chain under the constraint of cost, but also takes the negative impacts of economic activities on environment

as an important inspection item, embedding the awareness of environmental protection into supply chain management and pursuing the balance between economy and environment. Diverse criteria on economic and environmental aspects are vital in green supplier selection. Thus, the green supplier selection belongs to an MCDM problem, which is a major area of operations research and management science (Govindan et al., 2015; Liao et al., 2019a).

Three categories of techniques including the value theory-based methods, pairwise comparison based-outranking methods and decision rule-based methods have been investigated in solving MCDM problems (Liao et al., 2018). For MCDM problems concerning the GSCM, the first kind of techniques have been widely used, such as the TOPSIS, VIKOR, BWM, MOORA and MULTIMOORA. Among these value-based methods, the MULTIMOORA (Brauers & Zavadskas, 2010) is robust in using three subordinate utility functions, and is relatively easy, understandable and reliable for decision-makers (DMs). Because of these advantages, the MULTIMOORA has attracted significant attention after its appearance (Hafezalkotob et al., 2019). For complex decision problems with uncertain information, interval values, fuzzy numbers, rough numbers and linguistic terms were considered as the inputs of this method (Gou et al., 2017; Hafezalkotob et al., 2020; Liao et al., 2019b; Luo et al., 2019; Wu et al., 2018). However, little research was conducted regarding the stochastic input information in the MULTIMOORA framework. Although the uncertain input information can be captured by four types of above-mentioned data (intervals, fuzzy numbers, linguistic variables and rough numbers) in previous MULTIMOORA studies, there is still a challenge of allowing stochastic input data. As far as we know, only Akgül et al. (2017) combined the SMAA (Lahdelma & Salminen, 2001; Tervonen & Figueira, 2008; Pelissari et al., 2019) with the MOORA method by considering the second model (reference point model) in the MULTIMOORA framework. Given that the MULTIMOORA is of robustness with three subordinate utility functions, there is a need to combine the SMAA with MULTIMOORA to increase the flexibility of the MULTIMOORA method by accepting stochastic input information.

After obtaining three subordinate utilities of alternatives, three rankings of alternatives are subsequently generated. If three rankings of alternatives recommended to the DM are different, the DM may be confused by the three rankings and does not know which ranking is appropriate to make the decision. Brauers and Zavadskas (2010) noticed this problem and put forward the dominance theory to aggregate the three subordinate rankings. So far, there have been eleven different rank aggregation techniques (for details, please refer to Table 2) to tackle this issue (Hafezalkotob et al., 2020). Among these tools, the superior tool is the improved Borda rule (Wu et al., 2018), which enhances the Borda rule and makes up four limitations of dominance theory (Liao et al., 2019b). As for the improved Borda rule, the importance of different subordinate rankings, however, was neglected. The importance of different subordinate rankings shows the diverse attitudes of the DM to full, null and incomplete compensatory. The current improved Borda rule may be not apt to deal with the importance of different subordinate rankings in case that the importance information is provided. This is the second research gap.

Based on above analyses, this paper aims to use the SMAA to model the stochastic uncertain information for the input of MULTIMOORA. We introduce the MULTIMOORA into the utility aggregation model of the SMAA and name the new method as the SMAA-MULTIMOORA. This integrated method considers the reference point-based utility func-

tion, and also studies the ratio utility function and full multiplicative utility function. The improved Borda rule is enhanced to integrate three subordinate rankings calculated by three subordinate utility functions. To prove the validity and applicability of the proposed method, this paper applies it for the green supplier selection.

This study is structured as follows: Section 1 reviews the green supplier selection with MCDM methods, the MULTIMOORA method, and the SMAA. Section 2 presents the SMAA-MULTIMOORA method with the proposed ranking aggregation tool by the improved Borda rule and SMAA. A case study for the green supplier selection is provided in Section 3. The study ends with some conclusions.

1. Literature review

This section introduces the literature regarding MCDM methods in green supplier selection, the MULTIMOORA method and its variations, and the SMAA for illustrating current research gaps.

1.1. A survey of MCDM methods in green supplier selection

There is a vital relationship between green suppliers, green innovation and organizational environmental performance (Khaksar et al., 2016). In this regard, a primary concern of selecting green suppliers is how to rank candidate objectives with multiple criteria. MCDM techniques to tackle this issue have received considerable attention (Govindan et al., 2015). The literature regarding the selection of green supplier using MCDM methods published from 1997–2011 has been summarized by Govindan et al. (2015), which shows that the most commonly used method is AHP, and the fuzzy set theory is the commonly expression form of uncertain information. As far as we know, little follow-up research on MCDM techniques and green supplier selection was conducted. To find the latest research situation, we search the literature with respect to MCDM and green supplier selection from 2012 to 2019 in Web of Science database. The keyword for searching is "green supplier selection" and the time period is restricted from 2012 to 2019 to avoid the overlap with Govindan et al. (2015). In the filter process, we check the title and abstract of each paper for the relatedness of MCDM methods. After the manual filter process, we summarize the literature according to the number of criteria, the allowed uncertain information and the used MCDM approaches in Table 1.

In Table 1, 30 papers regarding the MCDM methods for the selection of green suppliers are tabulated. The average number of criteria which were taken into consideration is around eight. The number of multiple criteria in green supplier selection is greater than three, which satisfies the condition in MCDM problems. This also denotes that the MCDM techniques are apt to address the selection problem of green suppliers. In the third column, we can find that the uncertain information in green supplier selection was usually expressed as fuzzy numbers, which is accordant with the previous review (Govindan et al., 2015). Besides the fuzzy numbers, grey numbers also gained popularity in indicating uncertain information. Nevertheless, other expression forms of uncertain information such as the stochastic information may be neglected in green supplier selection with multiple criteria.

Table 1. Literature regarding the selection of green suppliers with MCDM methods published from 2012 to 2019

No.	Reference	Number of criteria	Uncertain information	MCDM approaches
1	Büyüközkan and Çifçi (2012)	5	Fuzzy numbers	ANP, DEMATEL, TOPSIS
2	Hsu et al. (2013)	13	–	DEMATEL
3	Shen et al. (2013)	10	Fuzzy numbers	TOPSIS
4	Kannan et al. (2014)	17	Fuzzy numbers	TOPSIS
5	Akman (2015)	5	Fuzzy numbers	FCM, VIKOR
6	Chithambaranathan et al. (2015)	8	Grey numbers	ELECTRE, VIKOR
7	Freeman and Chen (2015)	16	–	AHP, TOPSIS
8	Hashemi et al. (2015)	6	Grey numbers	ANP, GRA
9	Kannan et al. (2015)	11	Fuzzy numbers	AD
10	Awasthi and Kannan (2016)	16	Fuzzy numbers	VIKOR
11	Keshavarz Ghorabaee et al. (2016)	5	Fuzzy numbers	WASPAS
12	Govindan and Sivakumar (2016)	10	Fuzzy numbers	TOPSIS, MOLP
13	Liao et al. (2016)	5	Fuzzy numbers	AHP, ARAS, MSGP
14	Liou et al. (2016)	12	Grey numbers	ANP, DEMATEL, COPRAS
15	Bakeshlou et al. (2017)	17	Fuzzy numbers	ANP, DEMATEL, MOLP
16	Hamdan and Cheaitou (2017)	8	Fuzzy numbers	TOPSIS, AHP
17	Govindan et al. (2017)	5	–	PROMETHEE
18	Mohammadi et al. (2017)	14	Fuzzy numbers	Maximum deviation method
19	Mousakhani et al. (2017)	7	Fuzzy numbers	TOPSIS
20	Qin et al. (2017)	10	Fuzzy numbers	TODIM
21	Sang and Liu (2016)	7	Fuzzy numbers	TODIM
22	Sen et al. (2017)	6	Fuzzy numbers	MULTIMOORA
23	Yazdani et al. (2017)	8	–	DEMATEL, QFD, COPRAS, MOORA
24	Banaeian et al. (2018)	4	Fuzzy numbers	TOPSIS, VIKOR, GRA
25	Lo et al. (2018)	10	Fuzzy numbers	BWM, TOPSIS, MOLP
26	Tang and Wei (2018)	4	Fuzzy numbers	Bonferroni mean operator
27	dos Santos et al. (2019)	7	Fuzzy numbers	TOPSIS
28	Haeri and Rezaei (2019)	10	Grey numbers	BWM, GRA
29	Liu et al. (2019)	5	Fuzzy numbers	QFD, PBM operator
30	Lu et al. (2019)	13	Fuzzy numbers	Could model

Note: All abbreviations and corresponding explanations can be found in Table A.1 in the Appendix. – denotes on uncertain information in the MULTIMOORA-related methods. In other words, only crisp numbers without uncertainty are allowed as in put in these methods.

Till now, there is little research about the selection of green suppliers by MCDM methods with stochastic information. More specifically, the imperfect weights modeled by stochastic values have not been investigated although some sensitive analyses regarding the weights of criteria have been done. This is the first research gap of this paper. Considering the availability of stochastic information in some cases, this paper attempts to study the multiple criteria selection problem of green suppliers with stochastic evaluations of alternatives and stochastic evaluations on the weights of criteria.

1.2. A survey of the MULTIMOORA method and its extensions

From the fourth column of Table 1, we can find that the value-based MCDM methods play a vital role in green supplier selection with multiple criteria. Among these value-based MCDM methods, the MUTIMOORA method has only been studied once under fuzzy conditions in Sen et al. (2017), which reduces the efficiency of representing uncertain information in green supplier selection. To tackle this issue, this paper takes the stochastic information into consideration. We focus on the main features of the MULTIMOORA and its extensions with different uncertain information.

MULTIMOORA, stemming from MOORA, is a value theory-based MCDM method (Brauers & Zavadskas, 2010). It obtains the ranking of alternatives by three sub-aggregation utility functions, including the ratio utility function, reference point-based utility function and full multiplicative utility function. It contains three main stages: (1) normalization for the performance values of alternatives on different criteria, (2) computation for three kinds of utilities and obtaining subordinate ranks, and (3) aggregation the three subordinate rankings to obtain alternatives' ranking.

Firstly, the normalization of the alternatives' evaluations on each criterion should be done (Brauers & Zavadskas, 2006). The normalized evaluation value $\tilde{\xi}_{ij}$, whose value belongs to [0,1], can be computed by:

$$\tilde{\xi}_{ij} = \xi_{ij} \bigg/ \sqrt{\sum_{i=1}^{m} \xi_{ij}^2}. \tag{1}$$

The second step utilizes three utility functions to compute alternatives' utilities from different angles of compensatory.

The ratio utility function is devised based on the full compensatory aspect and its mathematical formula is shown as follows:

$$u_1(x_i, w) = \sum_{j=1}^{q} w_j \times \tilde{\xi}_{ij} - \sum_{j=q+1}^{n} w_j \times \tilde{\xi}_{ij}, \tag{2}$$

where $c_j (j = 1, 2, \cdots, q)$ belong to the benefit criteria and $c_j (j = q+1, q+2, \cdots, n)$ belong to the cost criteria.

The reference point-based utility function designs to capture alternatives' worst performances based on reference value on each criterion from the null compensatory aspect, shown in Eq. (3).

$$u_2(x_i, w) = \max_{j} w_j \left| \tilde{\xi}_{ij} - t_j \right|, \text{ with } t_j = \begin{cases} \max_{i} \tilde{\xi}_{ij}, & j \in \text{benefit} \\ \min_{i} \tilde{\xi}_{ij}, & j \in \text{cost} \end{cases}, \tag{3}$$

where the value of the reference point t_j varies with different kinds of criteria.

The full multiplicative utility function is designed as:

$$u_3\left(x_i,w\right)=\sum\nolimits_{j=1}^{q}\left(\tilde{\xi}_{ij}\right)^{w_j}\Bigg/\sum\nolimits_{j=q+1}^{n}\left(\tilde{\xi}_{ij}\right)^{w_j}. \tag{4}$$

Based on three obtained subordinate rankings, the alternatives' final ranking result can be deduced by different tools. In conclusion, the MULTIMOORA method is robust since it aggregates alternatives' performances by three utility functions from distinct compensatory points. Due to this, it has attracted much attention and many studies have been published. The relevant research has been summarized in two benchmarking reviews (Brauers & Zavadskas, 2012; Hafezalkotob et al., 2019). Table 2 lists the related research about MULTIMOORA from three angles: information forms of evaluations, weight determination methods for criteria and ranking aggregation tools.

In the second column, for uncertain situations, as far as we know, the stochastic uncertain information in performance evaluations is not allowed in the MULTIMOORA method. In the third column, the weights of criteria are mainly predetermined by DMs or computed by the BWM or AHP based on pairwise comparisons. These methods of determining the weights of criteria require a bunch of cognitive effort and time of DMs. To reduce the requirement of DMs, the uncertain performance values with stochastic distributions and missing or cardinal weights of criteria could be acceptable in the decision-making process. The second research gap appears. This motivates us to investigate stochastic input information in the MULTIMOORA method to increase its application scope.

Table 2. Comparisons of MULTIMOORA related research

Reference	Information form of evaluations	Weight determination method for criteria	Ranking aggregation tool
Brauers and Zavadskas (2010)	Crisp numbers	Predetermined weights	Dominance theory
Altuntas et al. (2015)	Crisp numbers	Predetermined weights	Dominance-directed graph; Borda rule; Rank position method
Lazauskas et al. (2015)	Crisp numbers	AHP	Arithmetic/geometric mean
Hafezalkotob et al. (2016)	Interval numbers	Predetermined weights	Dominance theory
Chen et al. (2018)	Linguistic terms	Predetermined weights	A non-linear optimization model
Dorfeshan et al. (2018)	Fuzzy numbers	AHP	Technique of precise order preference
Wu et al. (2018)	Probabilistic linguistic terms	Multiplicative AHP and correlation coefficients	Improved Borda rule
Hafezalkotob et al. (2020)	Interval numbers	BWM	Interval Borda rule
Liao et al. (2019b)	Hesitant fuzzy linguistic terms	AHP	ORESTE

In the last column, eleven methods to aggregate three subordinate rankings have been investigated for the final step of the MULTIMOORA method. Among these eleven methods, the dominance theory, firstly proposed by Brauers and Zavadskas (2010), is the most commonly used one (Hafezalkotob et al., 2019). As noted in Liao et al. (2019b), four limitations of the dominance theory have been proposed and these limitations can be tackled by the robust ORESTE method and the improved Borda rule (Wu et al., 2018). The ORESTE method is superior in considering cardinal relative importance of three subordinate rankings and leading less ties among alternatives, comparing with other nine aggregation methods. The improved Borda rule has advantages in considering every alternative's utility and its ranking position. The limitation of the improved Borda rule lies in overlooking the importance of three subordinate rankings. On the other hand, the ORESTE method only takes specific cardinal importance of the three subordinate rankings into consideration. For these ranking aggregation tools, the random cardinal importance or missing importance of three subordinate rankings are not acceptable. Fusing the advantages of the improved Borda rule and the ORESTE method and considering the random cardinal or missing importance of the three subordinate rankings by the SMAA are the third motivation of this paper.

1.3. A survey of stochastic multi-criteria acceptable analysis

The stochastic MCDM is of interest because it enables traditional MCDM techniques in tackling stochastic information and requires less crisp information in practice (Antucheviciene et al., 2015; Liang et al., 2018). Up to now, several effective methods have been emerged to tackle stochastic decision-making problems, such as the stochastic dominance method (Zaras, 2004; Ustinovichius & Simanaviciene, 2008), set pair analysis (Zou et al., 2013) and SMAA (Pelissari et al., 2019). The focus of this paper is the SMAA which is relatively easy to understand.

The SMAA is an efficient aid technique for tackling multi-criteria problems in case that only imperfect information is available (Lahdelma & Salminen, 2001). The uncertain input information can be modeled by two feasible space of criteria's weights W and alternatives' evaluation space $X_{m \times n}$. Stochastic variables w and ξ are designed to fit probability functions in these two feasible spaces. w and ξ denote the weight of a criterion and an alternative's stochastic performance on a criterion, respectively. For clear understanding, notations and corresponding explanations in this paper are tabulated in Table 3.

For the weight vector w in W, the summation of weights in the weight vector w should equal to one. As one more constraint is added in W, the dimension of W should be $n-1$ with the mathematical formula $W = \left\{ w \in R^n \middle| w_j \geq 0 \text{ and } \sum_{j=1}^{n} w_j = 1 \right\}$. If no preference of DMs is provided, the weights of criteria in W are supposed with the uniform distribution in [0, 1].

In the random sampling process of stochastic variables ξ and w, the utility of the alternative x_i can be calculated by simple additive weighting $u(x_i, \xi, w) = \sum_{j=1}^{n} w_j \xi_{ij}$. Then, we can obtain the rank of x_i by

$$rank(x_i, \xi, w) = 1 + \sum_{k \neq i} \rho\big(u(x_k, \xi, w) > u(x_i, \xi, w)\big), \tag{5}$$

where $\rho(\bullet)$ is a binary function whose value is either zero or one.

Table 3. Notations and explanations

Notations	Explanations
x_i, $i=1,2,\cdots,m$	m alternatives
c_j, $j=1,2,\cdots,q,q+1,q+2,\cdots,n$	n criteria with q benefit criteria and $n-q$ cost criteria
ξ_{ij}	The evaluations of the ith alternative on the jth criterion
t_j	The reference point value of alternatives on the jth criterion varies with the type of criteria
$\xi_{ij} \in X_{m\times n} = \left(\xi_{ij}\right)_{m\times n}$	The ith alternative's evaluation on the jth criterion
w_j	The weight of the jth criterion
w	The weight vector of criteria
$W = \left\{ w \in R^n \mid w_j \geq 0 \text{ and } \sum_{j=1}^{n} w_j = 1 \right\}$	The feasible space of criteria weights
$\rho(\bullet)$	A binary indicator function with only two values, zero and one
$u\left(x_i,\xi,w\right) = \sum_{j=1}^{n} w_j \xi_{ij}$	The utility of the ith alternative and the weight vector w
$rank\left(x_i,\xi,w\right)$	A function returns the rank position of alternative x_i's stochastic value ξ with the weight vector w
b_i^r	The rank acceptability index of alternative x_i ranked at position r
w_i^c	Alternative x_i's central weight vector
λ_τ^c, $\tau = 1,2,3$	The central importance vector of three subordinate rankings
p_i^c	The confidence vector of alternative x_i

With the ranks or rank requirements of alternatives, the feasible space W is limited by the rank function, $rank\left(x_i,\xi,w\right)$. $W_i^r\left(\xi\right) = \left\{ w \in W \mid rank\left(x_i,\xi,w\right) = r \right\}$ is a confined space, compared with $W = \left\{ w \in R^n \mid w_j \geq 0 \text{ and } \sum_{j=1}^{n} w_j = 1 \right\}$. In this area, the weight vector $w \in W_i^r\left(\xi\right)$ makes alternative x_i at the rth position.

The final result calculated by SMAA can be described by three measures, i.e., the acceptability index b_i^r, central weight vector w_i^c and confidence factor p_i^c.

The rth position-ranking acceptability index b_i^r of the alternative x_i can be calculated by

$$b_i^r = \int_{\xi \in X} f_X\left(\xi\right) \int_{w_i \in W_i^r\left(\xi\right)} f_W\left(w\right) dw d\xi, \tag{6}$$

where the values of stochastic variables ξ and w are generated by sampling in probability density functions, f_X and f_W. b_i^r ranges in $[0,1]$: One denotes that with the condition the weight vector w is given the alternative x_i definitely ranks at the rth position; Zero means that it is impossible for the alternative x_i to rank at the rth position with $w \in W_i^r\left(\xi\right)$.

The central weight vector w_i^c is devised based on the ranking acceptability index. The value of w_i^c can be determined by the centroid weights in $W_i^r\left(\xi\right) = \left\{ w \in W \mid rank\left(x_i,\xi,w\right) = r \right\}$ with the argument that the alternative x_i ranks first, shown as follows:

$$w_i^c = \frac{1}{b_i^1} \int_{\xi \in X} f_X(\xi) \int_{w \in W_i^1(\xi)} f_W(w)w\,dw\,d\xi, \tag{7}$$

where b_i^1 refers to the rank acceptability index of x_i ranking at the first position.

The confidence factor p_i^c denotes the probability that x_i ranks at the first position after two previous descriptive measures are determined. It can be computed by

$$p_i^c = \int_{\xi \in X: rank(x_i, \xi, w_i^c) = 1} f_X(\xi)\,d\xi. \tag{8}$$

Three mentioned above descriptive measures can be calculated theoretically by multi-dimensional integrals. However, computing the multi-dimensional integrals is very difficult in real situations by determining precise distribution on each dimension firstly and then integrating. The computational complexity exponentially increases with the number of dimensions. To avoid the considerable effort in computation, the approximate values of these multi-dimensional integrals are calculated by the Monte Carlo simulation. In this case, the computational complexity is not highly related with the number of dimensions in integrals (Milton & Arnold, 1995; Fishman, 1996; Keshavarz Ghorabaee et al., 2017a). Therefore, this paper also uses the Monte Carlo simulation to compute alternatives' three descriptive measures.

In the computation process of utilities of alternatives, the utility $u(x_i, \xi, w)$ of the alternative x_i can not only be calculated by the SAW model, $u(x_i, \xi, w) = \sum_{j=1}^{n} w_j \xi_{ij}$, but also can be computed by other utility models such as AHP, TOPSIS, VIKOR, PROMETHEE, ELECTRE (Pelissari et al., 2019) and EDAS (Keshavarz Ghorabaee et al., 2017b). To our knowledge, little study was given on the SMAA and the three utility functions of MULTIMOORA. Section 2 shows details regarding the SMAA-MULTIMOORA method.

2. The integrated methodology

The SMAA-MULTIMOORA method is proposed in this section to tackle uncertain input in the form of stochastic information. Three different utility functions are used for deriving alternatives' utilities from three aspects: full, null and incomplete compensatory. Then, the SMAA is used for aggregating the three rankings with stochastic importance values. The approximate value of multi-dimensional integrals in the SMAA is calculated by the Monte Carlo simulation. The SMAA-MULTIMOORA method's procedure is given step by step for application. Figure 1 illustrates the diagram of the SMAA-MULTIMOORA method.

Step 1: The stochastic input of alternatives' performance is acceptable in the SMAA-MULTIMOORA method. On the criteria angle, the missing or cardinal weights of criteria are also acceptable as well. This reduces the burden on DMs and increases their willingness to provide preference information. DMs provide additional assessments on alternatives or criteria if they want, but if DMs are not willing to give preference information on criteria's weights, the missing preference information is acceptable. The input in Step 1 is the basis for identifying the feasible space of Step 2.

Step 2: Identify the feasible weight space according to the preferences of DMs. If no preference information about the weights of criteria is given, the feasible weight space $W = \left\{ w \in R^n \middle| w_j \geq 0 \text{ and } \sum_{j=1}^{n} w_j = 1 \right\}$ is an $n - 1$ dimension-simplex over R^n.

Step 3: Stochastic samples in these feasible spaces W and X can be generated by corresponding distributions in the feasible space. $\wp = 1.96^2 / 4 \times limit\ error^2$ is the formula to determine the minimal iteration time $\wp$. *limit error* represents the tolerable error in the calculation process (Milton, & Arnold, 1995).

Step 4: Compute alternatives' utilities by three utility function in the MULTIMOORA. In each iteration, alternatives' utilities are computed by three utility functions in the MULTI-MOORA from different aspects of compensatory shown as Eqs (2)–(4).
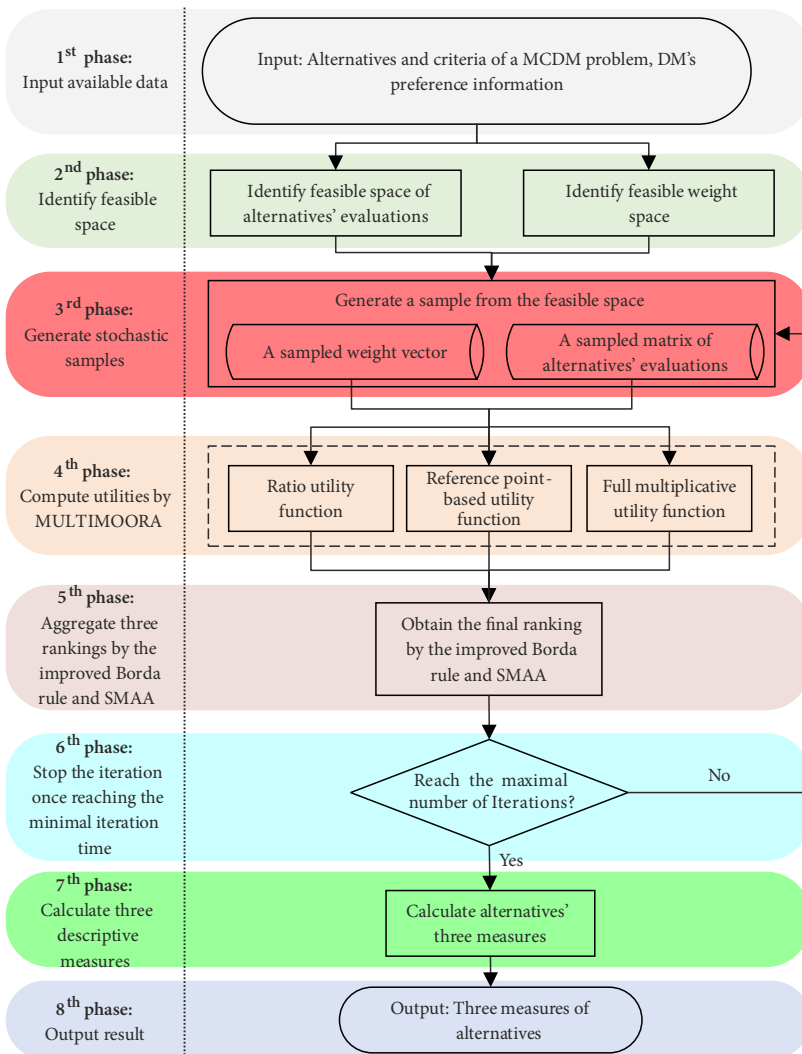

Figure 1. The diagram of the SMAA-MULTIMOORA method

Step 5: Aggregate the three rankings by the improved Borda rule and SMAA. In this step, the cardinal or missing importance of three subordinate rankings is considered by the SMAA thorough stochastically generating importance values satisfying the input constrains. The global utilities of alternatives could be computed by

$$u_G(x_i) = \lambda_1 \cdot \tilde{u}_1(x_i) \cdot \frac{m - r_1(x_i) + 1}{m(m+1)/2} - \lambda_2 \cdot \tilde{u}_2(x_i) \cdot \frac{r_2(x_i)}{m(m+1)/2} + \lambda_3 \cdot \tilde{u}_3(x_i) \cdot \frac{m - r_3(x_i) + 1}{m(m+1)/2},$$

(9)

where λ_1, λ_2, and λ_3 indicate the importance values of three rankings, respectively. If $\lambda_1 = \lambda_2 = \lambda_3 = 1$, Eq. (9) reduces to the improved Borda rule in Wu et al. (2018). The final ranking outcomes of Step 5 are the data base of Step 7.

Step 6: If the minimal iteration time $\wp$ is reached, then stop the iteration and go to Step 7; otherwise, go to Step 3. Monte Carlo simulations run 10000 times in this paper.

Step 7: Calculate three descriptive measures, b_i^r, w_i^c and p_i^c, by Eqs (6)–(8) after executing the minimal iteration time.

Step 8: Output the values of b_i^r, w_i^c and p_i^c and ends the procedure.

The SMAA-MULTIMOORA method contains eight steps for obtaining the final decision result of alternatives. Step 1 and Step 8 do the data input and output, respectively. Step 2 processes the input data to identify two key feasible space with or without the DM's preference information. Step 3 generates the sample data stochastically. Step 4 uses the sampled data for computing utilities by the three utility functions in the MULTIMOORA. Step 5 aggregates three rankings with cardinal or missing information on the importance values of three rankings. Step 6 checks whether the iteration reaches the minimal iteration times $\wp$ or not. Step 7 computes the SMAA-MULTIMOORA method's descriptive measures. Step 8 outputs three descriptive measures of alternatives and ends the procedure.

3. Case study

This section solves a selection problem of green suppliers regarding the economic, environmental and social criteria by the SMAA-MULTIMOORA method. Comparative analyses with other stochastic techniques, different ranking aggregation tools and uncertain MULTIMOORA variants are provided in Section 3.3.

3.1. Case description

While in traditional supply chain management, maximizing an enterprise's economic benefits is the primary goal, enterprises are now more and more aware of the increasingly prominent environment problems and the sense of social responsibility for developments. Under the background of pursuing the development of economic benefits, how to coordinate the balanced development of enterprise's economic benefits, environmental benefits and social benefits has become an urgent problem. In the GSCM, green suppliers, as the upstream enterprises, can influence the supply chain by producing eco-friendly upstream products,

reducing the production cost and offering volunteer service for the society. Generally speaking, green suppliers is vital in the GSCM.

The evaluation of green suppliers can be considered from three aspects: economy, environment and society. Different research took diverse criteria into consideration. Considering the average number of criteria in literature from 2012 to 2019 is eight, in this paper, we select eight most widely used criteria from economic, environmental and social perspectives and their explanations are listed in Table 4. These eight criteria are summarized from the papers listed in Table 1 and also from the previous survey (Govindan et al., 2015).

The first three criteria, the fourth to sixth criteria, and the seventh and eighth criteria are based on economic consideration, environmental consideration, and social consideration, respectively. Among these eight criteria, the first criterion is in cost type while the others are benefit type. The cost, product quality and delivery reliability are assumed to follow the

Table 4. Criteria and descriptions

Criteria	Descriptions
c_1 Cost	The cost of the enterprise to obtain products refers to the price of the products to the factory. On the premise that the product quality and delivery time meet the requirements of purchasers, the supplier's product price can reflect the supplier's willingness to cooperate and its competitive advantage.
c_2 Product quality	Product quality refers to the ability of green suppliers to provide demand-meeting products. If the products provided by a green supplier cannot meet the technical specification, the supplier will not be included in the list of qualified suppliers.
c_3 Delivery reliability	Due to the great instability of the market and the fluctuation of enterprise inventory in each node of the supply chain, it is very important to consider the delivery reliability of the supplier. Greater delivery reliability means that the supplier has stronger production management capability and the supplier has stronger response capability to sudden changes in the supply chain.
c_4 Environmental management system	As the most commonly considered criterion in the literature published from 1997 to 2011 (Govindan et al., 2015), environmental management system can be considered through the certification of the environmental protection system, production of ecologically efficient, ecological design requirements for energy products, and compliance with local laws and policies.
c_5 Green image	The green image can be reflected through the implementation of the environmental responsibility of the enterprise to the supplier, the public's views on the environmental related problems of the supplier, the cooperation relationship with the green organization, and the green commitment of top managers.
c_6 Waste management	The nature of waste is an economic waste, which does not achieve the objective of maximizing the efficiency of resource use. Taking waste disposal into consideration can effectively alleviate the contradiction between the current shortage of resources and economic development.
c_7 Social responsibility	Green supply chain achieves both commercial profits and environmental protection by establishing long-term cooperation. This is also the basis for enterprises to transform their partners in the supply chain to be in charge of responsibility to the society.
c_8 Information disclosure	Information disclosure refers to the open and transparent extent of green suppliers in the SCM to the public. The disclosure of green information can build the communication and trust between enterprises, upstream and downstream suppliers, and public stakeholders.

normal distribution with corresponding means and variances. In addition, other performance values are supposed to be uniformly distributed with intervals. Other distributions of stochastic input data are accepted by the proposed method as well. Interval distribution and normal distribution are taken as examples to illustrate the applicability. In this case study, four green suppliers are considered as alternatives.

3.2. Solve the problem by the SMAA-MULTIMOORA

Next, the problem is solved by the SMAA-MULTIMOORA.

Step 1: Alternatives' evaluations are assumed to be stochastic values with normal distributions and uniform distributions, tabulated in Table 5. The preference information about criteria weights is supposed to be unknown.

Table 5. Four alternatives' evaluations on eight criteria

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
x_1	N(5,1)	N(7,1)	N(8,1)	U(4,5)	U(6,7)	U(6,7)	U(4,5)	U(7,8)
x_2	N(5.5,1)	N(4,1)	N(9,1)	U(1,3)	U(5,6)	U(5,7)	U(7,8)	U(6,7)
x_3	N(7,0.2)	N(6,1)	N(7,2)	U(7,8)	U(5,7)	U(2,3)	U(6,7)	U(4,5)
x_4	N(3,1)	N(5,1.5)	N(7,1)	U(5,7)	U(4,5)	U(7,8)	U(6,7)	U(5,6)

Step 2: Identify the feasible space. Criteria's weights are assumed to uniformly distribute in the $n-1$ simplex $W = \left\{ w \in R^n \middle| w_j \geq 0 \text{ and } \sum_{j=1}^{n} w_j = 1 \right\}$. The feasible evaluation space $X_{m \times n}$ can be identified by the values in Table 5.

Steps 3–6: Generate stochastic samples, compute alternatives' utilities by the MULTIMOORA method, aggregate three alternatives' subordinate rankings by Eq. (9) and stop the iteration once reaching the minimal iteration time. We repeat Steps 3–6 10000 times as iteration.

Steps 7–8: The values of three descriptive measures are calculated by Eqs (6)–(8) according to the computation data in 10000 times, and displayed in Tables 6–7 and Figure 2.

Table 6. Alternatives' ranking acceptability indices computed by our method

b_i^r	Rank 1	Rank 2	Rank 3	Rank 4
x_1	0.4835	0.3738	0.1227	0.0200
x_2	0.0641	0.1442	0.3636	0.4281
x_3	0.0622	0.1167	0.3284	0.4927
x_4	0.3902	0.3653	0.1853	0.0592

As shown in Figure 2, the alternative x_1 obtains the highest rank acceptability index in the first rank position. Similarly, alternatives' ranking is obtained as $x_1 \succ x_4 \succ x_2 \succ x_3$, and the confidence factor p_i^c also supports the ranking result.

Table 7. Alternatives' confidence factors and central weight vectors computed by our method

| Alter-native	Central weight vector w_i^c								Confidence factor p_i^c	Central importance vector λ_τ^c		
	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8				
x_1	0.1226	0.4835	0.1260	0.1115	0.1385	0.1241	0.0994	0.1381	0.4835	0.3375	0.3400	0.3225
x_2	0.1359	0.0641	0.1607	0.0510	0.1247	0.1162	0.1835	0.1365	0.0641	0.3235	0.3999	0.2766
x_3	0.1082	0.0622	0.1354	0.1841	0.1421	0.0480	0.1562	0.0906	0.0622	0.3110	0.4092	0.2798
x_4	0.1308	0.3902	0.1143	0.1458	0.1073	0.1391	0.1420	0.1103	0.3902	0.3369	0.3002	0.3629
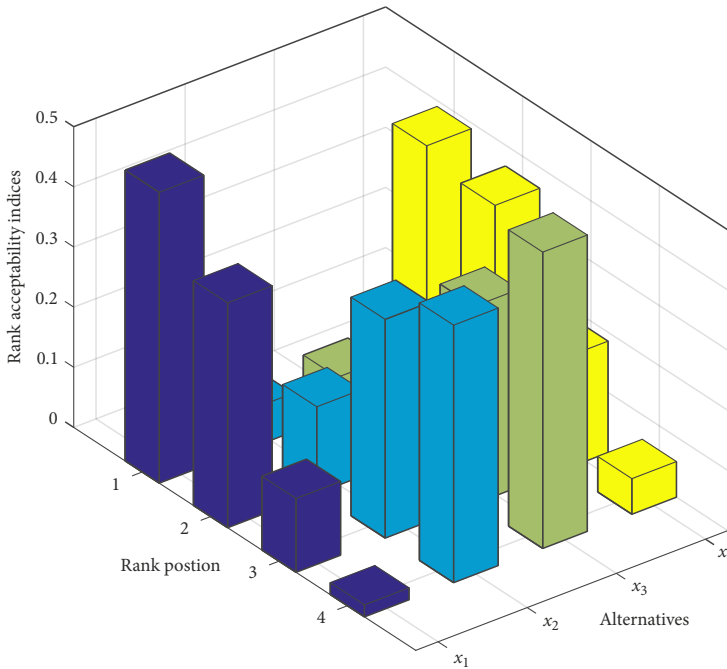
Figure 2. Alternatives' ranking acceptability index calculated by the SMAA-MULTIMOORA method

3.3. Comparative analyses

In this section, the problem is solved by other related techniques including the stochastic techniques, SMAA and SMAA-MOORA, the different ranking aggregation tool, the improved Borda rule, and other uncertain MULTIMOORA variant, the interval MULTIMOORA method. Comparative analyses among these methods are given to verify the efficiency and robustness of our method.

3.3.1. Comparisons with other stochastic techniques

In this section, the existing SMAA (Lahdelma & Salminen, 2001) and SMAA-MOORA (Akgül et al., 2017) methods are used to solve the problem with different utility functions to tackle the input information.

Because the SMAA and SMAA-MOORA have the ability to tackle stochastic information, the same stochastic input information can be handled by the SMAA and SMAA-MOORA methods. The main results computed by the SMAA and SMAA-MOORA methods are showed in Tables 8 and 9 and Figure 3(a) and 3(b).

Table 8. Alternatives' ranking acceptability indices computed by the SMAA and SMAA-MOORA methods

SMAA	Rank 1	Rank 2	Rank 3	Rank 4	SMAA-MOORA	Rank 1	Rank 2	Rank 3	Rank 4
x_1	0.5363	0.3001	0.1265	0.0371	x_1	0.4185	0.3506	0.1922	0.0387
x_2	0.1361	0.2496	0.3099	0.3044	x_2	0.1483	0.1859	0.244	0.4218
x_3	0.2499	0.2656	0.2352	0.2493	x_3	0.1893	0.1879	0.2787	0.3441
x_4	0.0777	0.1847	0.3284	0.4092	x_4	0.2439	0.2756	0.2851	0.1954

Table 9. Alternatives' ranking acceptability indices computed by the SMAA and SMAA-MOORA methods

	Confidence factor p_i^c	Central weight vector w_i^c							
		c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
SMAA									
x_1	0.5363	0.1157	0.1377	0.1215	0.1133	0.1331	0.1376	0.1012	0.1400
x_2	0.1361	0.1372	0.0889	0.1541	0.0704	0.1149	0.1340	0.1740	0.1266
x_3	0.2499	0.1514	0.1218	0.1184	0.1642	0.1237	0.0812	0.1398	0.0995
x_4	0.0777	0.0834	0.1177	0.1145	0.1628	0.0949	0.1777	0.1524	0.0968
SMAA-MOORA									
x_1	0.4185	0.1303	0.1368	0.1277	0.1137	0.1284	0.1368	0.0945	0.1317
x_2	0.1483	0.1472	0.1001	0.1437	0.0504	0.1303	0.1362	0.1570	0.1352
x_3	0.1893	0.1496	0.1316	0.1204	0.1640	0.1350	0.0610	0.1413	0.0972
x_4	0.2439	0.0804	0.1132	0.1136	0.1651	0.1167	0.1435	0.1412	0.1264

The SMAA method obtains the ranking of alternatives as $x_1 \succ x_3 \succ x_2 \succ x_4$. The SMAA-MOORA method acquires the ranking result as $x_1 \succ x_4 \succ x_3 \succ x_2$. In these two calculation results, only the rank position of alternative x_1 is the same and the ranks of the other alternatives are quite different, which is consistent with the different heights of histogram in Figures 3(a) and 3(b).

3.3.2. Comparisons with the aggregation function of the improved Borda rule

In this section, a different ranking aggregation tool, the improved Borda rule (Wu et al., 2018), is adopted to integrate the three subordinate rankings of alternatives.

The improved Borda rule is used by setting three parameters in Eq. (9) as one, $\lambda_1 = \lambda_2 = \lambda_3 = 1$. The calculated results can be seen in Table 10 and Figure 4.
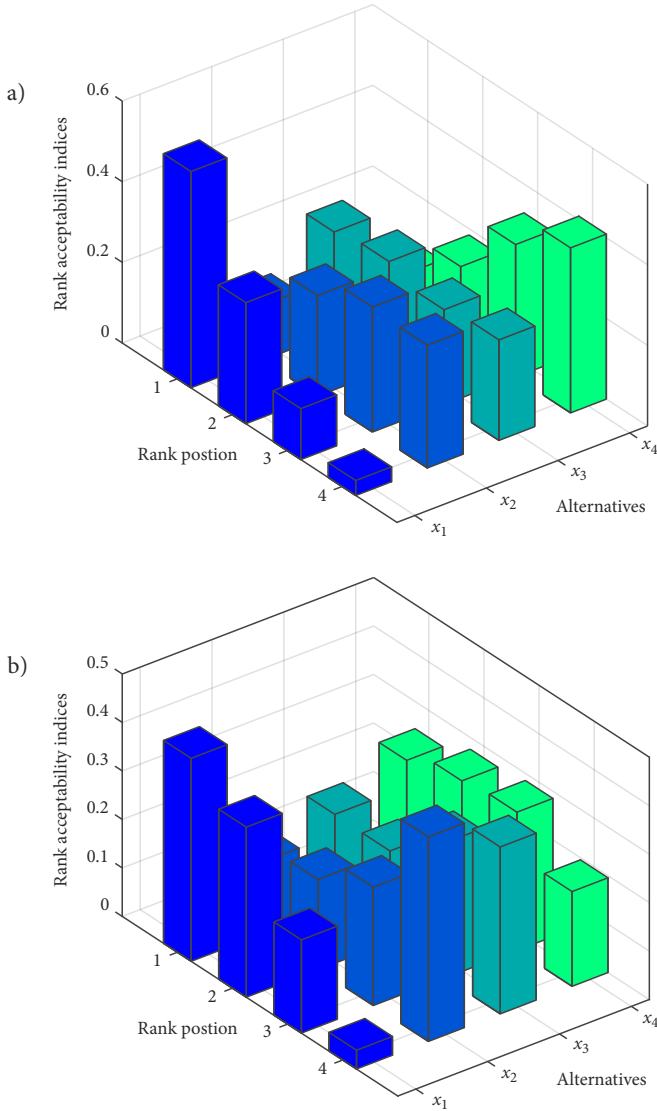
Figure 3. Ranking acceptability index calculated by: a) the SMAA method;
b) the SMAA-MOORA method

Table 10. The ranking acceptability index of alternatives computed by the improved Borda rule

	Confidence factor p_i^c	Rank 1	Rank 2	Rank 3	Rank 4
x_1	0.5021	0.5021	0.3587	0.1215	0.0177
x_2	0.0609	0.0609	0.1364	0.3662	0.4365
x_3	0.0488	0.0488	0.1047	0.3435	0.5030
x_4	0.3882	0.3882	0.4002	0.1688	0.0428
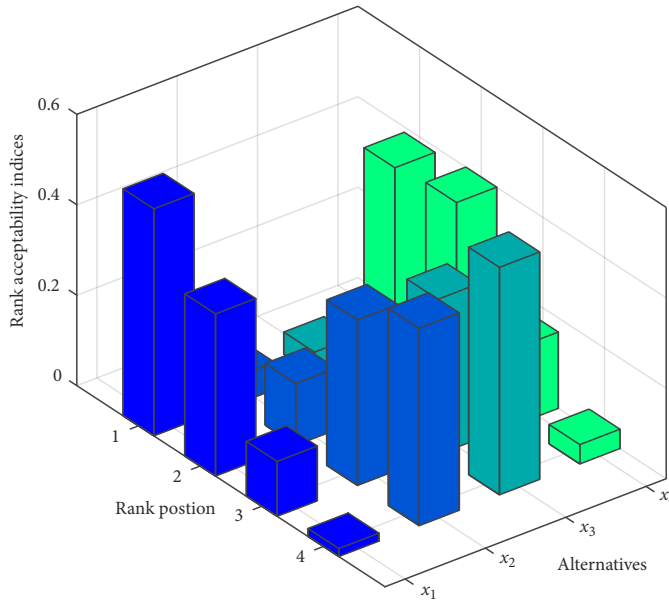
Figure 4. Ranking acceptability index calculated by the improved Borda rule

Both the ranking acceptability index and confidence factor show the same ranking of alternatives as that derived by the proposed SMAA-MULTIMOORA method. The difference between these two different integration tools is that the tool in the SMAA-MULTIMOORA method can consider the importance of three subordinate rankings, thus further reflecting the attitude towards the acceptability to compensatory by the central importance vector λ_τ^c and making the decision-making results easy to understand, while the improved Borda rule only considers the situation in which the three rankings are equally important.

3.3.3. Comparisons with interval MULTIMOORA method

Since the interval MULTIMOORA method is not able to deal with the stochastic input information, the data in Table 5 is transformed into Table 11 based on the properties of the normal distribution and uniform distribution.

The transformed data in Table 11 can be computed by the interval MULTIMOORA method with the assumption of equal weights on the eight criteria (Hafezalkotob et al., 2016). The ranking result computed by the interval MULTIMOORA method is $x_1 \succ x_4 \succ x_2 \succ x_3$, which is the same as the ranking derived by the SMAA-MULTIMOORA method.

Table 11. Alternatives' transformed interval evaluations on eight criteria from Table 5

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
x_1	[2,8]	[4,10]	[5,11]	[4,5]	[6,7]	[6,7]	[4,5]	[7,8]
x_2	[2.5,8.5]	[1,7]	[6,12]	[1,3]	[5,6]	[5,7]	[7,8]	[6,7]
x_3	[6.4,7.6]	[3,9]	[1,13]	[7,8]	[5,7]	[2,3]	[6,7]	[4,5]
x_4	[0,6]	[0.5,9.5]	[4,10]	[5,7]	[4,5]	[7,8]	[6,7]	[5,6]

3.4. Insights and discussions

In this section, we try to get some insights through the above calculation results to demonstrate the validation and robustness of the SMAA-MULTIMOORA method. Some enlightenments for green supplier selection are provided as well.

(1) Validation of the SMAA-MULTIMOORA method

As for alternative x_1, no matter what method is used, it always ranks first. For the other alternatives, the computation results of the SMAA-MULTIMOORA method and interval MULTIMOORA method are the same, but the rankings of alternatives obtained by the SMAA method and SMAA-MOORA method are significantly different. The same ranking is because the interval MULTIMOORA method deals with uncertain information by considering the mid-point values in the intervals, while the SMAA-MULTIMOORA method makes use of the distribution of uncertain information so that the random input information can be used in the decision-making process. The different ranking is due to the different consideration angles about the compensation effect: the SMAA method is allowed to accept the compensatory effect fully by the ratio system model, and the SMAA-MOORA method permits the non-compensatory effect by using the reference point model to reject alternatives which own a smaller value on a certain criterion. The SMAA-MULTIMOORA method not only considers the two above models, but also takes the incomplete compensatory effect into consideration by the full multiplicative model. The random input information and the compensation effects from three aspects are the significant properties regarding the validation of our method.

(2) Robustness of the SMAA-MULTIMOORA method

The robustness of the SMAA-MULTIMOORA method lies in different aspects, including the robustness of the original MULTIMOORA method by three utility functions, its acceptability to stochastic information, its integration tool with stochastic importance of three subordinate rankings, and the improved Borda rule. The robustness of the MULTIMOORA method has been shown by many studies (Brauers & Zavadskas, 2010, 2012; Hafezalkotob et al., 2019). The ability to process uncertain information comes from the SMAA method, which has a pivotal role in solving stochastic MCDM problems (Lahdelma & Salminen, 2001; Tervonen & Figueira, 2008; Pelissari et al., 2019). The robust ranking aggregation tool fusing with the improved Borda rule and the SMAA method makes the cardinal or missing importance information on the importance of the three subordinate rankings acceptable. The final ranking of alternatives is recommended by a ranking acceptability index of alternatives, which makes the result easy to understand.

In total, the SMAA-MULTIMOORA method owns two advantages in validation and robustness, which allows the analyses of the MULTIMOORA method with imperfect data in the statistical way and is able to judge the robustness of the results calculated by the MULTMOORA method.

(3) Enlightenments for green supplier selection

This study provides a feasible approach to select green suppliers when only stochastic data is accessible. The technique of tackling stochastic data relaxes the constraints and reduces

the burden of DMs in providing information about suppliers. The SMAA-MULTIMOORA method is able to use the available suppliers' information as much as possible. The uncertain information of the performance values of alternatives on each criterion is acceptable in this case study. Although the final ranking result is calculated based on the uncertain information, it shows the clear discrepancy among alternatives. More specifically, the first alternative x_1 has a 48.35% probability of being the optimal alternative while the alternative x_4 ranks at the first position with the probability 39.02%. In the case that no additional preference information of DMs is given, the alternative x_1 should be chose instead of the alternative x_4. In another case that the DMs provide extra preference information of suppliers, the interactive decision-making process will continue to find alternatives' ranking. In the selection of green suppliers by traditional MCDM methods with crisp numbers, only the certain ranking result of alternative is provided for DMs to make decisions. In the selection of green suppliers with uncertain information, usually the midpoints of uncertain intervals are employed to calculate the final ranking of alternatives. Compared with the previous uncertain green supplier selection problems, the less requirements for providing precise information and the more informative ranking result are two advantages of the green supplier selection problem with stochastic information solved by the SMAA-MULTIMOORA method.

Conclusions

Investigating the selection of green supplier is a continuous concern within the GSCM framework, and the selection of green suppliers can be realized by considering multiple criteria, which is a classical characteristic of MCDM techniques. Focusing on the multiple criteria green supplier selection problem, this paper summarized the relevant research from 2012 to 2019. Based on the survey, we defined the research target as computing stochastic input information in the MULTIMOORA method for obtaining robust results. This paper presented an SMAA-MULTIMOORA method. On the one hand, this method makes the SMAA method consider three utility functions from full, null and incomplete compensatory aspects; on the other hand, it also allows the stochastic input information in the framework of MULTIMOORA. The case study verifies the efficient of the method. The robustness of the SMAA-MULTIMOORA method is verified by some comparative analyses.

For future research, the interaction of criteria modelled by the Choquet integral (Choquet, 1953) and the applications for sorting problems with large number of alternatives would be interesting issues.

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Author contributions

Xiaomei MI and Huchang LIAO conceived the study and were responsible for the design and development of the data analysis. Xiaomei MI, Huchang LIAO, Yi LIAO and Qi LIN were

responsible for data collection and analysis. Xiaomei MI and Huchang LIAO were responsible for data interpretation. Xiaomei Mi, Huchang LIAO and Qi LIN wrote the first draft of the article. Yi LIAO, Benjamin LEV and Abdullah AL-BARAKATI checked and revise the draft.

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APPENDIX

Table A.1. Abbreviations and explanations

Abbreviation	Explanation
AD	Axiomatic Design
AHP	Analytic Hierarchical Process
ANP	Analytic Network Process
BWM	Best Worst Method
COPRAS	COmplex PRoportional ASsessment
DEMATEL	DEcision MAking Trial and Evaluation Laboratory
DM	Decision Maker
EDAS	Evaluation based on Distance from Average Solution
ELECTRE	ELimination Et Choix Traduisant la REalité in French, ELimination and Choice Expressing the Reality
FCM	Fuzzy c-means clustering method
FMOO	Fuzzy Multi-ObjectiveOptimization
GRA	Grey Relational Analysis
GSCM	Green Supply Chain Management
MCDM	Multiple Criteria Decision Making
MOLP	Multi-Objective Linear Programming
MSGP	Multi-segment goal programming
MULTIMOORA	Multi-Objective Optimization by Ratio Analysis plus the full MULTIplicative form
ORESTE	Oorganísation, rangement et Synthèse de données relarionnelles in French, Organization, Arrangement and Synthesis of Relational Data in English
PBM	Partitioned Bonferroni mean
PROMETHEE	Preference Ranking Organization METHod for Enrichment of Evaluations
QFD	Quality Function Deployment
SAW	Simple Additive Weighting
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 (Multiple criteria optimization compromise solution in English)
WASPAS	Weighted Aggregated Sum Product Assessment