Hindawi
Discrete Dynamics in Nature and Society
Volume 2019, Article ID 2456260, 14 pages
https://doi.org/10.1155/2019/2456260

Research Article

Resilient Supplier Selection Based on Fuzzy BWM and GMo-RTOPSIS under Supply Chain Environment

Jiawu Gan,[1] **Shuqi Zhong**,[1] **Sen Liu**,[2] **and Dan Yang**[1]

[1] *International Business School, Yunnan University of Finance and Economics, Kunming 650221, China*
[2] *School of Logistics, Yunnan University of Finance and Economics, Kunming 650221, China*

Correspondence should be addressed to Jiawu Gan; andy_gan@ynufe.edu.cn

Received 28 January 2019; Accepted 12 March 2019; Published 7 April 2019

Academic Editor: Paolo Renna

Resilient suppliers can reduce supply chain risk, effectively avoid supply chain disruption, and bring profits to enterprises. However, there is no united measuring index system to evaluate the resilient supplier under supply chain environment, and the assessment language sets are usually crisp values. Therefore, in order to fill the research gap, this paper proposes a hybrid method, which combines triangular fuzzy number, the best-worst method (BWM), and the modular TOPSIS in random environments for group decision-making (GMo-RTOPSIS) to solve the above problem. Firstly, the weight of decision-maker is calculated by using fuzzy BWM which can deal with triangular fuzzy numbers. Secondly, triangular fuzzy number is introduced into GMo-RTOPSIS, and combined with fuzzy BWM, alternatives are sorted to select the best resilient supply chain partner. Finally, the feasibility and universality of this method are proved by illustrative examples.

1. Introduction

As a result of globalization, supply chains are confronted with natural disasters, man-made disasters, and technological threats at any time [1]. These disasters will cause supply chain interruption and shortage of raw materials, such as floods and other natural disasters, and the gradual increase of timber costs; these disasters lead to fluctuations in raw materials quality and interruption of delivery dates, resulting in supply chain fluctuations [2, 3]. Man-made/technological disasters such as fires, traffic accidents, technology leaks, and terrorist attacks can also lead to supply chain disruption, and increasing supply chain resilience can alleviate the disruption problem. Since suppliers are the main external risks of supply chain, how to choose resilient suppliers becomes an effective way to avoid supply chain interruption [4, 5].

Holling [6] first proposed the concept of resilience and pointed out that resilience is the ability to absorb change. Subsequently, Scholar believes that elasticity should be defined as the ability of enterprises to deal with inevitable disasters, linking elasticity with absorptivity and resilience. Yang and Xu [7] preferred to define resilience as the ability of an enterprise to respond to natural disasters; the resilience can be assessed by the rate of recovery. Through literature review, resilience is a necessary factor in the selection of suppliers, and how to choose more resilient suppliers has become the research object of scholars. Sustainable development of enterprises is related to how to deal with disruption situations, and the choice of resilient suppliers is an important factor in dealing with interruption situation properly [8]. Choosing suppliers with good quality can enhance the resilience of supply chain and reduce the overall risk of supply chain [5]. At present, for most scholars from the perspective of improving supply chain to improve resilience [9–12], research has become mature. A few scholars have begun to evaluate resilient suppliers from the perspective of the capabilities they need before, when and after disruption, which is more scientific. As a relatively blank research area, this paper chooses the absorptive capacity, adaptive capacity, and restorative capacity described as the selection criteria of resilient suppliers.

Rajesh and Ravi [4] uses grey relational analysis to calculate the grey possibility value and select resilient suppliers. Valipour Parkouhi and Safaei Ghadikolaei [5] chose price fluctuation, vulnerability, supplier capacity limit, and visibility as indicators and determined supplier's elasticity level by combining fuzzy analysis network process and grey VIKOR. Haldar et al. [13] combined fuzzy TOPSIS and fuzzy weight method to select resilient suppliers, which can reduce the vulnerability of supply chain system. Pramanik et al. [14] uses AHP-TOPSIS-QFD to measure supplier performance in order to select a resilient supplier.

However, through literature review, we find that the supplier selection in resilient supply chain still has limitations. Firstly, few studies have been conducted on the selection of resilient suppliers. Secondly, many multiattribute decision-making methods strongly restrict the freedom of decision-makers to use the type of information, which greatly reduces the personal opinions of relevant decision-makers. Thirdly, in most studies, decision-makers have to reach an agreement on criteria, which is difficult to achieve. Fourthly, crisp number cannot accurately describe the decision-maker's evaluation of alternatives. Therefore, in order to fill the research gap, we proposed a method combining fuzzy BWM and improved TOPSIS to determine the weight of decision-makers and rank the alternatives for supplier selection in resilient supply chain. Finally, the practicability of this method is proved by the illustrative example.

The structure of this paper is divided into seven parts. The second section is literature review; the third section proposes the evaluation criteria of resilient supplier selection under supply chain environment. Section four introduces the preliminaries including some definitions. The proposed method is proposed in the fifth section. Section six introduces the illustrative example. Finally, the conclusions are presented in section seven.

2. Literature Review

Some early researchers defined resilience as the ability of a system to recover from disruption [15, 16]. In the definition of resilience by scholars Allenby and Fink [17] and Pregenzer [18], the ability of the system to maintain function in the disaster is emphasized. Haimes [19] proposed the definition of resilience refers to the ability of withstand the disruption and recovery with reasonable time and costs. After that, scholars state that the key to enhancing resilience is that the supply chain process should be managed and put forward the principle of building a resilient supply chain [20, 21]. Holcomb and Ponomarov [22] proposed that logistics capacity is related to resilience; coordination and integration capabilities can enhance the ability to confront disruption. Maklan and Jüttner [23] argued that risk management and knowledge management have an impact on resilience. Hosseini et al. [24] proposed the method of literature classification and, through literature review, studied the application domain of resilience and identified four areas of resilient application: organizational domain, social domain, economic domain, and engineering domain. Papadopoulos et al. [11] emphasized the role of swift trust, public-private partnerships, and quality of information sharing in promoting supply chain resilience.

Supplier selection is an important issue in the resilient supply chain and daily operation of enterprises. It is regarded as a strategic choice of enterprises [25] and also a difficult and complex process [26]. In the 1990s, scholars began to study the selection of business suppliers. Subsequently, scholars subdivided the selection of suppliers, such as the choice of sustainable suppliers and resilient suppliers, and the criteria considered in the selection process changed accordingly. However, scholars have not reached a consensus on the selection criteria of resilient suppliers. Christopher and Peck [20] discussed the upstream inventory and supply conditions on impact of supply chain resilience. Rajesh and Ravi [4] considered that when choosing resilient suppliers, the key factors that should be considered include: vulnerability, collaboration, risk awareness, and supply chain continuity management. Baek et al. [27] argued that the driving factor of resilient supply chain is flexibility, while Tamvakis et al. [28] emphasize the role of transportation. Vugrin et al. [29] define resilience from the perspectives of predisruption prevention and postdisruption recovery and considered that resilience includes absorptive, adaptive, and restorative capacities. Scholar Hosseini extends the content of resilience, subdivides the criteria of absorptive, adaptive, and restorative capacities in different application domain, quantifies the resilience of inland waterway ports and sulfuric acid manufacturer with Bayesian network, and studies the selection of resilient suppliers [30–32].

Supplier selection essentially is a multiattribute decision-making problem, and there are many methods to deal with such problems in the field of supply chain, for example, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and improved TOPSIS [25, 33–35], Analytic Hierarchy Process (AHP) and its extension [25, 26, 36], ANP [37], Data Envelopment Analysis (DEA) and its improvement [38–40], VIKOR [5, 41, 42], and best-worst multicriteria decision-making method (BWM) [43, 44]. BWM has only been proposed in recent years; the relevant research is relatively blank, which is a direction of great research value.

BWM is proposed by Rezaei [45]; compared with AHP, BWM needs less data for comparison, and the final result is consistent with AHP [46]. BWM greatly reduces the complexity of calculation. And through more consistent comparisons, the final result will be more credible. However, the traditional BWM cannot determine the weight in uncertain environment [47], so scholars have improved BWM, and fuzzy BWM has been developed [48–50]. BWM based on triangular fuzzy numbers is one of them. BWM has been used in many areas and has solved some practical problems, such as evaluating the service quality of baggage handling systems [51], cloud service selection [52], identifying success factors in eXtensible Business Reporting Language (XBRL) [53], performance evaluation and ranking of airports [54], identifying the research and development (R&D) of enterprises [55], assessment of the technologies for the treatment of urban sewage sludge [56], etc.

As a common method, TOPSIS is proposed by Hwang and Yoon [57]. The principle of TOPSIS is to make the ideal solution as close to positive-ideal solution (PIS) as possible and as far away from negative-ideal solution (NIS) as possible. However, the traditional TOPSIS still has some limitations. It can only deal with the information of a single decision-maker and can only have crisp numbers in the decision matrix. In order to expand the research field of TOPSIS, scholars have proposed improved TOPSIS methods, such as TOPSIS which can deal with interval numbers [58–60], TOPSIS containing fuzzy information [61–63], combination of TOPSIS and intuitionistic fuzzy information [64], and TOPSIS method which can process information of multiple decision-makers [62, 64–67]. One of the most important method, GMo-RTOPSIS proposed by Lourenzutti and Krohling [68], has been applied to a wider range of research areas. It has the following advantages. (1) It can process decision information in dynamic environment. (2) Unlike traditional TOPSIS, GMo-RTOPSIS divides decision matrix into smaller modules, each module can use different information types, and there is no need to unify the information types. (3) In addition to crisp numbers, it can handle random variables. (4) Decision-makers need not discuss together to get a set of criteria; each decision-maker can decide the criteria in the decision matrix independently. (5) Information of multiple decision-makers can be processed simultaneously.

Literature review shows that there are still limitations in the selection of resilient suppliers. (1) Studies on supplier selection criteria focus more on cost, raw material quality, science technology, and services. Nowadays, supply chain is in a changing environment; resilient suppliers must have the ability to cope with disruptions. Responsiveness, risk reduction, geographical segregation, and other capabilities should be considered in the selection of resilient suppliers [1]. Therefore, how to use appropriate tools to select resilient suppliers has become an important research object. (2) The language of the decision-makers and its difficulty in accurately describing lead to the deviation of the results of weight calculation and alternatives ranking. (3) When the areas of decision-makers are different, the unified criteria and weights of alternatives become unattainable. Decision-makers have different evaluation criteria and weights on the alternatives, and the final results take into account the comprehensiveness and scientificity of the alternatives.

Therefore, in order to fill the research gap, this paper introduces the selection of resilient suppliers in supply chain, combining triangular fuzzy number, best-worst method (BWM), and the Modular TOPSIS in random environments for group decision-making (GMo-RTOPSIS). Fuzzy BWM is introduced into multicriteria decision-making problems to calculate decision-makers' weights more accurately. GMo-RTOPSIS is used to calculate the decision matrix given by decision-makers independently, and the suppliers of resilient supply chain are ranked according to the decision-makers' weight obtained by fuzzy BWM. Finally, an example is given to verify the effectiveness of the proposed method.

The reason why we integrate fuzzy BWM with TOPSIS is that the combination of the two methods makes the selection process simpler and the results more consistent and scientific. The specific reasons are as follows. (i) As the latest MAGDM method, BWM has the advantages of simpler calculation process and more reliable weight distribution results compared with other methods. For example, the AHP method has similar principles with BWM [45], but AHP uses pairwise comparison. In the process of data comparison, it compares more times than BWM and involves fraction, which increases the computational complexity. At the same time, the BWM can remedy the inconsistency acquired from pairwise comparisons [48]. The procedure of BWM is much easier, more precise, and at less redundant due to the fact that it does not involve secondary comparisons compared with other methods [45]. (ii) As a multiattribute decision-making method, TOPSIS has better performance than the other eight methods. Zanakis et al. [69] compared eight MAGDM methods: simple additive weighting (SAW), elimination (et) and choice translating reality (ELECTRE), multiplicative exponential weighting (MEW), TOPSIS and four AHPs by a simulation study, and discovered that TOPSIS, SAW, and MEW performed best and ELECTRE was the worst. Moreover, Peng and Xiao [70] and Sun et al. [71] pointed out that TOPSIS is a better decision-making skill for choosing alternatives because of its clear and understandable logic. TOPSIS can also deal with qualitative and quantitative problems well [72]. At the same time, the improved modular TOPSIS has the ability to deal with multiattribute decision-making problems in dynamic environment, it can also deal with decision-making information of multiple decision-makers, and it does not require each decision-maker to have the same criteria, which greatly improves the freedom of decision process and the credibility of the final results [68]. Besides, due to triangular fuzzy number being able to solve the problem of incomplete and inaccurate information in the process of calculating weights and ranking alternatives, we integrate BWM, GMo-RTOPSIS, and triangular fuzzy numbers to solve the resilient supplier selection problem under supply chain environment.

3. The Criteria of Resilient Supplier Selection under Supply Chain Environment

Actively resilient planning of supplier can reduce the possibility of disruption of supply chain system in the event of disruptions [13]. Torabi et al. [8] argued that natural or man-made disasters would change the selection process and indicators of suppliers. They distinguished the selection of traditional suppliers from resilient suppliers and developed a new decision model for resilient supplier selection. This paper considers the supplier selection criteria of resilient supply chain from the perspective of impact of natural/man-made disasters.

Vulnerability and recovery are two dimensions of resilience, and the main difference between the two dimensions is before and after the disruption [73–75]. Vulnerability refers to the system's resistant preparation and ability before disruption occurs. Recovery refers to how the system adapts to situations when disruption occurs and how to repair the system until normal operation. Vulnerability and recovery constitute resilience, which enables the resilient system to better respond to the whole process of disaster. In absorptive, adaptive and restorative capacity proposed by Vugrin et al. [29], the adaptive ability and restorative ability constitute recoverability [32]. This paper refers to the criteria proposed by [76] for selection of resilient suppliers. The criteria include

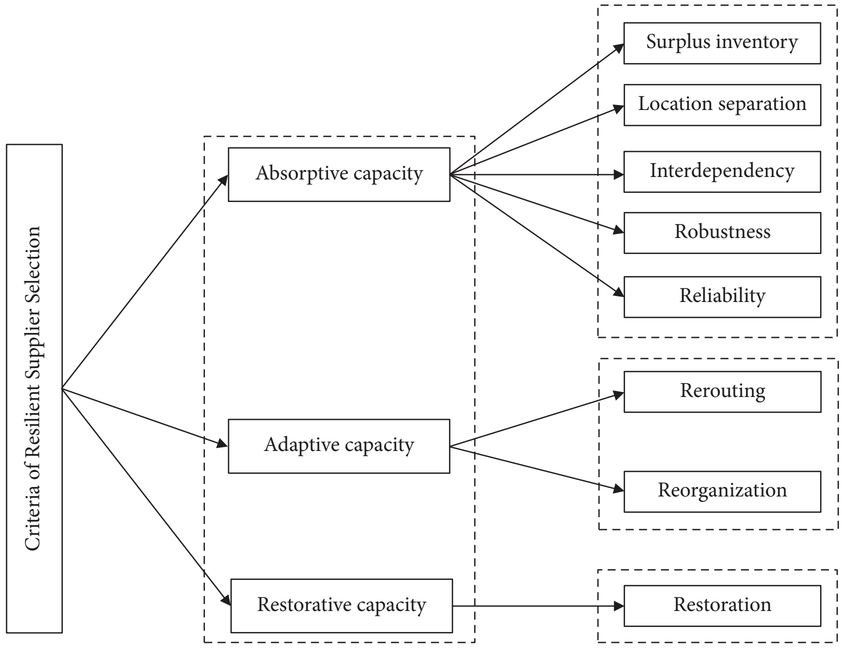

Figure 1: The criteria of resilient supplier selection under supply chain environment.

the absorptive capacity, adaptive capacity, and restorative capacity and their subcriteria for suppliers before, during, and after disasters [76]. The largest number of subprojects included is absorptive capacity, which means that suppliers must invest a lot of money to improve absorptive capacity before disruptive events occur, in order to absorb the damage caused by shocks to the greatest extent when shocks occur. Restorative capacity, as an after-event maintenance, requires suppliers to spend enough manpower and capital to repair the damage, which belongs to the postevent repair, so this content is single and less important than absorptive capacity and adaptive capacity. Figure 1 illustrates the criteria of resilient supplier selection under supply chain environment [76].

3.1. Absorptive Capacity. It is helpful for resilient supply chain management [77] for suppliers to take appropriate measures to prevent risks before they realize them. With the change of supply chain environment, the selection criteria of suppliers need to be updated. Hosseini and Barker [31] considered supplier's absorptive capacity as an important capability and examined the supply chain's resilience, adaptability to the environment, and rebuilding ability from the perspective of absorbency. Absorptive capacity mainly aims at improving suppliers before disruptive events, so as to achieve its own ability to resist disruptions. The evaluation of absorptive capacity is mainly divided into the following five aspects.

(i) Surplus Inventory. Whether the supplier has surplus inventory is an important reflection of absorptive capacity. The presence of surplus inventory is the basic condition for manufacturers to quickly resume production and repair supply chains in the event of natural/man-made disasters. Surplus inventory can make up for the production interruption, and the supply chain will not end immediately. It allows enterprises to have a competitive advantage among many suppliers.

(ii) Location Separation. Location separation requires enterprises to have separate production areas and spare production areas. When disaster occurs, other production areas should quickly replenish their products to ensure that the supply chain is not interrupted.

(iii) Interdependency. Interdependency is mainly embodied in the backup supplier contract. The standby supplier refers to the fact that the enterprise must select the standby supplier before the disruptive event occurs. After the disruptions, it can establish a contract relationship with the standby supplier in time, without causing the termination of production and quickly make up for the loss of production caused by the disruptive event.

(iv) Robustness. Robustness indicates that supplier's building in production area must have certain physical protection. When disaster occurs, it can reduce the damage to equipment and products and improving the resilience.

(v) Reliability. The more reliable the supplier is, the less likely it will be impacted by man-made disasters. Reliability requires suppliers to provide reliable raw materials on time in their daily operations and to have confidence in their accounts. Reliability is an important project of absorptive capacity as a preparation in advance.

3.2. Adaptive Capacity. For supplier selection in resilient supply chain, not only should economic factors such as cost and quality be considered, but also whether suppliers can respond to changes in the environment [78]; adaptive capacity has become an important condition for evaluating supplier resilience. In resilient supply chain, flexibility has become an important indicator to be considered in the selection process, where flexibility includes that suppliers can quickly change the original route and restructure and adapt to the changed supply chain in the shortest possible time [79]. Levalle and Nof [80] argued that team building is conducive to improving resilience; while emphasizing the important role of cooperation, supplier-competitor cooperation can prevent supply chain disruption under the necessary circumstance.

Absorptive capacity emphasizes the ability of suppliers to withstand disruptions before they occur. When disasters occur, absorptive capacity becomes ineffective, and adaptive capacity becomes the ability to assess how suppliers adapt to the environment through their own changes. The absorptive capacity is embodied in the ability of supply chain reorganization, which requires suppliers to have certain flexibility to standardize and modularize products so that disruptive events can be quickly reorganized and repaired [81].

(i) Rerouting. When disruptions occur, suppliers can only adapt to changing environmental conditions by changing themselves; rerouting is an important aspect. Rerouting refers to enterprises changing the usual mode of transport; fast combination of multiple modes of intermodal transport ensures the normal transportation of goods and the operation of supply chain. Changing the mode of transportation means that costs increase, but it can prevent supply chain interruption and improve the flexibility of enterprises in the supply chain.

(ii) Reorganization. When the organization is damaged, suppliers can quickly pool resources and acquire the ability to adapt to the new environment and rebuild the organization and corporate culture. In this case, the organization can cooperate temporarily with its competitors to compensate for the impact of other factors on the supply chain.

3.3. Restorative Capacity. Restorative capacity is the least appealing of the three abilities that resilient suppliers should possess; because postdisaster reconstruction has little effect on disruption prevention and resistance, suppliers only with postdisaster reconstruction capability will increase the economic losses caused by disruptions.

RC refers to the ability of suppliers to repair and quickly restore production after a disruptive event. Technical support from suppliers is an important manifestation of restorative capacity [82].

(i) Restoration. The main indicators of restorations are mainly divided into four aspects. Firstly, the enterprise has enough maintenance fund and maintenance equipment. Then, it needs sufficient technical personnel to complete the maintenance process. Finally, the enterprise should have the ability to quickly make up for the market vacancies caused by the disruptions.

4. Preliminaries

In this section, we will introduce some mathematical concepts that may appear in the decision matrix of the GMo-RTOPSIS and provide some ways of normalization, defuzzification, calculating distance, and comparison size.

4.1. Fuzzy Set. Fuzzy set was proposed by Zadeh in 1965. It converts the crisp value of the evaluation problem into an interval on the axis. Fuzzy set is used to deal with the problem in uncertain environment. We provide some basic conceptions of fuzzy set in the next section.

Definition 1 (see [83]). Let $\tilde{a}$ be an fuzzy set in the universe of discourse X, where $\tilde{a} = \{\langle x, \mu_{\tilde{a}}(x)\rangle : x \in X\}$. $\mu_{\tilde{a}}$ is a membership function $\mu_{\tilde{a}} : X \longrightarrow [0,1]$, where $\mu_{\tilde{a}}(x) \leq 1\ \forall x$.

4.2. Triangular Fuzzy Set

Definition 2. let $\tilde{a} = (a_1, a_2, a_3)$ be a triangular fuzzy set (TrFN), where $a_1 < a_2 < a_3$.

Definition 3 (see [84, 85]). let $\tilde{a} = (a_1, a_2, a_3)$ be a TrFN; the defuzzified value of $\tilde{a}$ is as follows:

$$R(\tilde{a}) = \frac{a_1 + 4a_2 + a_3}{6} \tag{1}$$

Definition 4 (see [86]). let $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ be two TrFN; then the distance between them is given by

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}\sum_{i=1}^{3}(a_i - b_i)^2} \tag{2}$$

Definition 5. When $R(\tilde{a}) > R(\tilde{b})$, we say $\tilde{a}$ is superior to $\tilde{b}$. By contraries, $\tilde{a}$ is indifferent to $\tilde{b}$ if $R(\tilde{a}) = R(\tilde{b})$.

Definition 6. Let $\tilde{a}_{ij} = (a_{ij}^1, a_{ij}^2, a_{ij}^3)$ be a TrFN, the normalization of $\tilde{a}_{ij}$ is given by the following formula:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}^1}{\max_i a_{ij}^3}, \frac{a_{ij}^2}{\max_i a_{ij}^3}, \frac{a_{ij}^3}{\max_i a_{ij}^3}\right), \quad i = 1, \cdots, m \tag{3}$$

5. The Proposed Method

The research method proposed in this paper consists of three steps: in the preparation stage, the reference comparison matrix of decision-makers is established, and the comparison results are presented in the form of triangular fuzzy numbers. The second stage is aggregating, using triangular fuzzy numbers to improve BWM and determine the weight of decision-makers based on fuzzy BWM. The third step is the selection stage. A new TOPSIS method, namely, GMo-RTOPSIS, is introduced to deal with the decision matrix provided by the decision-makers. By dealing with the decision matrix containing different information types, a better scheme is obtained. Figure 2 illustrates the conceptual framework of the proposed approach.

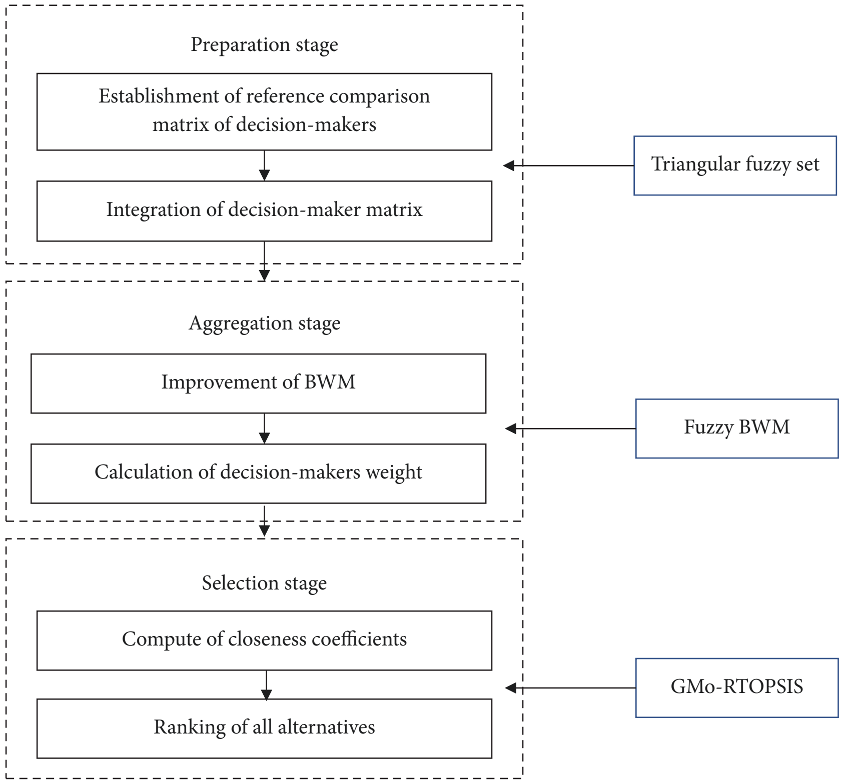

Figure 2: The conceptual framework of the proposed approach.

5.1. Collection of Decision Opinions and Establishing Decision Matrices. Let $M = \{1, 2, \cdots, m\}$, $N = \{1, 2, \cdots, n\}$, $K = \{1, 2, \cdots, k\}$. Let $\mathbf{A} = \{A_1, A_2, \cdots, A_m\} (m \geq 2)$ represent a total of m alternatives and $C = \{C_1, C_2, \cdots, C_n\}$ denotes the n criterion of $\mathbf{A}$. $\widetilde{w}^* = (\widetilde{w}_1^*, \widetilde{w}_2^*, \cdots, \widetilde{w}_k^*)$ is the weight of a group of decision-makers, where $\sum_{d=1}^{k} \widetilde{w}_d = 1, d \in K$. $\mathbf{Y}$ is a random vector which effects $\mathbf{A}$. Let $s_{ij}^{(d)}(\mathbf{Y}^{(d)})$ denote the ratings s_{ij} are related to random vector $\mathbf{Y}$. Notice in particular that $s_{ij}^{(d)}$ and $s_{lj}^{(d)}$ must be the same type of information. The evaluation information of A_i according to C_j provided by decision-maker $DM^{(d)}$ is $DM^{(d)}(\mathbf{Y}) = (s_{ij}^{(d)}(\mathbf{Y}^{(d)}))$, $(i \in M, j \in N, d \in K)$.

So, each $DM^{(d)}$ will provide its individual decision matrix $DM^{(d)}(\mathbf{Y})$ including interval-numbers and triangular fuzzy set (TrFN). Moreover, each matrix is allowed to consider different criterion C_j.

$$\mathrm{DM}^{(d)}\left(\mathbf{Y}^{(d)}\right) = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} s_{11}^{(d)}\left(\mathbf{Y}^{(d)}\right) & s_{12}^{(d)}\left(\mathbf{Y}^{(d)}\right) & \cdots & s_{1n}^{(d)}\left(\mathbf{Y}^{(d)}\right) \\ s_{21}^{(d)}\left(\mathbf{Y}^{(d)}\right) & s_{22}^{(d)}\left(\mathbf{Y}^{(d)}\right) & \cdots & s_{2n}^{(d)}\left(\mathbf{Y}^{(d)}\right) \\ \vdots & \vdots & \ddots & \vdots \\ s_{m1}^{(d)}\left(\mathbf{Y}^{(d)}\right) & s_{m2}^{(d)}\left(\mathbf{Y}^{(d)}\right) & \cdots & s_{mn}^{(d)}\left(\mathbf{Y}^{(d)}\right) \end{bmatrix} \end{array}, \quad d = 1, \cdots, k \tag{4}$$

5.2. Weighting for Decision-Makers Based on Fuzzy BWM. Best-worst method is proposed by Rezaei [45], which can solve multiattribute decision-making problem. The principle of this method is to replace secondary comparisons with reference comparisons, thus reducing n^2 comparison results to $2n - 3$ for simplifying the comparison process. Traditional BWM is only used to deal with crisp values. After improvement by scholars [48], BWM can deal with multiattribute decision-making problems in fuzzy environment. Comparisons of criteria are described as linguistic labels where the linguistic terms are expressed in triangular fuzzy numbers, which make the results much closer to the real ideas of decision-makers.

The operation steps of fuzzy BWM are as follows.

Firstly, compare the weights from k decision-makers and assume there are k decision-makers $\{d_1, d_2, \ldots, d_k\}$.

Secondly, d_B represents the best (most important) DM under all criteria, and the worst (least important) DM is expressed as d_W.

Thirdly, determine the fuzzy preferences of the best over all the DMs by using the linguist labels in Table 1 [87]. Similarly, all the DMs over worst can be obtained by this step

$$\widetilde{\mathrm{A}}_{\mathrm{B}} = (\widetilde{a}_{B1}, \widetilde{a}_{B2}, \cdots, \widetilde{a}_{Bk}) \tag{5}$$

$$\widetilde{\mathrm{A}}_{W} = (\widetilde{a}_{1W}, \widetilde{a}_{2W}, \cdots, \widetilde{a}_{kW}) \tag{6}$$

Among them, $\widetilde{\mathrm{A}}_{\mathrm{B}}$ is vector of Best-to-Others and Others-to-Worst is labeled as $\widetilde{\mathrm{A}}_W$ where $\widetilde{a}_{Bj} = (h_{Bj}, k_{Bj}, l_{Bj})$ represents

Table 1: Transformation rules of linguistic variables of decision-makers.

Linguistic terms	Membership function
Equally important(EI)	(1,1,1)
Weakly important(WI)	(2/3, 1, 3/2)
Fairly important(FI)	(3/2, 2, 5/2)
Very important(VI)	(5/2, 3, 7/2)
Absolutely important(AI)	(7/2, 4, 9/2)

TrFN preference of d_B over decision-maker j and $\widetilde{a}_{iW} = (h_{iW}, k_{iW}, l_{iW})$ express TrFN preference of decision-maker i over d_W. Obviously $\widetilde{a}_{BB} = (1, 1, 1)$.

Fourthly, we use fuzzy linguistic terms to indicate the weight of decision-maker j as $\widetilde{w}_j = (h_j^w, k_j^w, l_j^w)$, in which $\widetilde{w}_B = (h_B^w, k_B^w, l_B^w)$ ($\widetilde{w}_W$) reflects the weight of the most important (least important) decision-makers.

Fifth, we get the optimal fuzzy weight $(\widetilde{w}_1^*, \widetilde{w}_2^*, \cdots, \widetilde{w}_k^*)$ through the following formula

$$\begin{aligned} \min \quad & \beta \\ s.t. \quad & \left| \frac{\widetilde{w}_B}{\widetilde{w}_j} - \widetilde{a}_{Bj} \right| \leq \beta \\ & \left| \frac{\widetilde{w}_j}{\widetilde{w}_W} - \widetilde{a}_{jW} \right| \leq \beta \\ & \sum_{j=1}^{n} R\left(\widetilde{w}_j\right) = 1 \\ & h_j^w \leq k_j^w \leq l_j^w \\ & h_j^w \geq 0 \\ & j = 1, 2, \cdots, n \end{aligned} \tag{7}$$

where $\beta = (h^\beta, k^\beta, l^\beta)$. In order to transform the TrFN weight of DM to crisp weight, we use the $R = (\widetilde{w}_j) = (h_j^w + 4k_j^w + l_j^w)/6$.

The (7) can be transferred as [48]

$$\begin{aligned} \min \quad & \beta^* \\ s.t. \quad & \left| \frac{(h_B^w, k_B^w, l_B^w)}{(h_j^w, k_j^w, l_j^w)} - \left(h_{Bj}, k_{Bj}, l_{Bj}\right) \right| \leq (p^*, p^*, p^*) \\ & \left| \frac{\left(h_j^w, k_j^w, l_j^w\right)}{(h_W^w, k_W^w, l_W^w)} - \left(h_{jW}, k_{jW}, l_{jW}\right) \right| \leq (p^*, p^*, p^*) \\ & \sum_{j=1}^{n} R\left(\widetilde{w}_j\right) = 1 \\ & h_j^w \leq k_j^w \leq l_j^w \\ & h_j^w \geq 0 \\ & j = 1, 2, \cdots, n \end{aligned} \tag{8}$$

where $\beta^* = (p^*, p^*, p^*)$, $p^* \leq h^\beta$. By solving (8), we obtained the weights of all the DMs $(\widetilde{w}_1^*, \widetilde{w}_2^*, \cdots, \widetilde{w}_k^*)$.

5.3. GMo-RTOPSIS for Alternative Evaluation. Hwang and Yoon [88] proposed the TOPSIS theory, which is a common method to solve MAGDM problems in static environment. The DMs need to unify the criteria in advance, which limit the freedom of decision-making. The first step of TOPSIS is to normalize the decision matrix and then aggregate the attribute weight into the matrix to get the normalized matrix with weight. The NIS and PIS $r_j^{(d)+/-}(\mathbf{Y})$ under each criterion are selected. Then, calculate the separation measures $S_i^{+/-}(\mathbf{Y})$ for each alternative, and the last step is to convert $S_i^{+/-}(\mathbf{Y})$ into closeness coefficients CC_i by formula; the bigger the CC_i, the better the alternative.

After years of development, traditional TOPSIS has been unable to deal with more variable MAGDM problems. So scholars expand TOPSIS, such as Modular-TOPSIS, and TOPSIS with intuitionistic fuzzy set. GMo-RTOPSIS is proposed by Lourenzutti and Krohling [68]. As the extension of TOPSIS, GMo-RTOPSIS can deal with the independent decision matrix provided by decision-makers without discussion. In the decision matrix, each decision-maker can consider different criteria, use different information types for diverse decision criterion, and also deal with the information types relate to random variables. GMo-RTOPSIS is more accurately expressing decision-makers' evaluation of alternatives and broadens the traditional TOPSIS.

The operation steps of GMo-RTOPSIS are as follows:

Firstly, each $DM^{(d)}$ will provide his/her decision matrix $DM^{(d)}(\mathbf{Y}), d \in K$.

Secondly, based on the above results, the next step is normalizing each $DM^{(d)}(\mathbf{Y}), d \in K$ from the k decision-makers. Refer to (3) for normalization methods for TrFN; then $DM^{(d)}(\mathbf{Y})^*, d \in K$ is obtained.

Thirdly, calculate $r_j^{(d)+}(\mathbf{Y})$ (positive-ideal solution) and $r_j^{(d)-}(\mathbf{Y})$ (negative-ideal solution) for every $DM^{(d)}(\mathbf{Y}), d \in K$, and criterion. Generally there is

$$r_j^{(d)+}(\mathbf{Y}) = \max\left\{r_{1j}^{(d)}(\mathbf{Y}), \cdots, r_{mj}^{(d)}(\mathbf{Y})\right\}, \quad j \in N \tag{9}$$

$$r_j^{(d)-}(\mathbf{Y}) = \max\left\{r_{1j}^{(d)}(\mathbf{Y}), \cdots, r_{mj}^{(d)}(\mathbf{Y})\right\}, \quad j \in N \tag{10}$$

Compute the separation measures for each $\mathbf{A} = (A_1, A_2, \cdots, A_m)$

$$S_i^+(\mathbf{Y}) = \sqrt{\sum_{d=1}^{k}\sum_{j=1}^{n_d}\left[\widetilde{w}_d^* w_j^{(d)} d\left(r_j^{(d)+}(\mathbf{Y}), r_{ij}^{(d)}(\mathbf{Y})\right)\right]^2}, \quad i \in M \tag{11}$$

$$S_i^-(\mathbf{Y}) = \sqrt{\sum_{d=1}^{k}\sum_{j=1}^{n_d}\left[\widetilde{w}_d^* w_j^{(d)} d\left(r_j^{(d)-}(\mathbf{Y}), r_{ij}^{(d)}(\mathbf{Y})\right)\right]^2}, \quad i \in M \tag{12}$$

Among them, $\widetilde{w}_d^*$ denotes the weight of the dth decision-maker based on fuzzy BWM method. $w_j^{(d)}$ is weight of jth criterion given by dth decision-maker in respective matrix.

Fourthly, we can obtain closeness coefficients for each $\mathbf{A} = (A_1, A_2, \cdots, A_m)$ as follows:

$$CC_i = \frac{S_i^-(\mathbf{Y})}{S_i^-(\mathbf{Y}) + S_i^+(\mathbf{Y})} \tag{13}$$

Finally, rank the $\mathbf{A} = (A_1, A_2, \cdots, A_m)$ using degree of dominance $A_i > A_j$, if $P(C_i(\mathbf{Y}) > C_j(\mathbf{Y})) > P(C_j(\mathbf{Y}) > C_i(\mathbf{Y}))$.

5.4. The Main Steps of the Proposed Method. The approach of proposed method is summarized as follows.

Step 1. Select the most important DM(d_B) and least important DM(d_W) in all decision-makers $\{d_1, d_2, \dots, d_k\}$.

Step 2. Compute vector of Best-to-Others $\widetilde{\mathrm{A}}_{\mathrm{B}}$ and Others-to-Worst $\widetilde{\mathrm{A}}_W$ based on TrFN.

Step 3. Calculate the optimal weight $(\widetilde{w}_1^*, \widetilde{w}_2^*, \cdots, \widetilde{w}_k^*)$ of each decision-maker by (8).

Step 4. k decision-makers provide their decision matrix $DM^{(d)}(\mathbf{Y}), d \in K$ individually.

Step 5. According to (3) normalize each $DM^{(d)}(\mathbf{Y}), d \in K$ from the k decision-makers; we get $DM^{(d)}(\mathbf{Y})^*, d \in K$.

Step 6. Calculate $r_j^{(d)+}(\mathbf{Y})$ (PIS) and $r_j^{(d)-}(\mathbf{Y})$ (NIS) for every $DM^{(d)}(\mathbf{Y})^*, d \in K$, and criterion by (9) and (10).

Step 7. Compute the separation measures $S_i^+(\mathbf{Y})$ and $S_i^-(\mathbf{Y})$ for each alternative $\mathbf{A}$ by (11) and (12).

Step 8. Obtain closeness coefficients CC_i for each alternative $\mathbf{A}$ in (13).

Step 9. Rank the alternative $\mathbf{A} = (A_1, A_2, \cdots, A_m)$ using degree of dominance and select the better alternative A_i.

6. Illustrative Examples and Discussion

6.1. Illustrative Example. This paper takes H company's supplier selection in the resilient supply chain environment as an example. Assuming that three decision-makers (d_1, d_2, d_3) scored four alternative suppliers (A_1, A_2, A_3, A_4) and three decision-makers had different views on resilient supplier selection, decision-maker one focused on the absorptive capacity before the risk occurred, decision-maker 2 focused more on how suppliers changed themselves to adapt to the environment when the disruptions occurred, and decision-maker 3 considered that postdisaster reconstruction was also the key step to restore the normal operation of supply chain. H company cannot identify the weights of the three decision-makers, and M consulting company calculates the weights of its decision-makers.

Table 2: The linguistic label for fuzzy preferences of the best criterion over all the criteria.

Criteria	d_1	d_2	d_3
Best criterion d_1	EI	VI	AI

Table 3: The linguistic label for fuzzy preferences of all the criteria over the worst criterion.

Criteria	Worst criterion d_3
d_1	AI
d_2	FI
d_3	EI

There are eight criteria in total, which reflect absorptive capacity, adaptive capacity, and restorative capacity. The criteria selected by the three decision-makers can be overlapping and repetitive. C_1-surplus inventory, C_2-location separation, C_3-interdependency, C_4- robustness, C_5-reliability, C_6-rerouting, C_7-reorganization, and C_8-restoration.

Step 1. The 'first decision-maker' (d_1) and 'third decision-maker' (d_3) are, respectively, the best and the worst criterion based on M company's decision.

Step 2. According to the transformation rules, the fuzzy reference comparisons are executed. Tables 2 and 3 illustrate the fuzzy preferences of Best-to-Others and Others-to-Worst based on Table 1; we can transfer the linguistic terms in Tables 2 and 3 to membership function $\widetilde{\mathrm{A}}_{\mathrm{B}}$ and $\widetilde{\mathrm{A}}_W$ as follows:

$$\begin{aligned}\widetilde{\mathrm{A}}_{\mathrm{B}} &= \left[(1,1,1), \left(\frac{5}{2}, 3, \frac{7}{2}\right), \left(\frac{7}{2}, 4, \frac{9}{2}\right)\right] \\ \widetilde{\mathrm{A}}_W &= \left[\left(\frac{7}{2}, 4, \frac{9}{2}\right), \left(\frac{3}{2}, 2, \frac{5}{2}\right), (1,1,1)\right]\end{aligned} \tag{14}$$

Step 3. Based on the above analysis, for getting the weights of three decision-makers, the problem can be built according to (8).

Next, we bring the data from Steps 1 and 2 into the formula and get the following inequalities.

$$\begin{aligned} \min \quad & \beta^* \\ \text{s.t.} \quad & \left|\frac{(h_1^w, k_1^w, l_1^w)}{(h_3^w, k_3^w, l_3^w)} - (h_{13}, k_{13}, l_{13})\right| \le (p^*, p^*, p^*) \\ & \left|\frac{(h_1^w, k_1^w, l_1^w)}{(h_2^w, k_2^w, l_2^w)} - (h_{12}, k_{12}, l_{12})\right| \le (p^*, p^*, p^*) \\ & \left|\frac{(h_1^w, k_1^w, l_1^w)}{(h_1^w, k_1^w, l_1^w)} - (h_{11}, k_{11}, l_{11})\right| \le (p^*, p^*, p^*) \end{aligned}$$

$$\left|\frac{(h_1^w, k_1^w, l_1^w)}{(h_3^w, k_3^w, l_3^w)} - (h_{13}, k_{13}, l_{13})\right| \le (p^*, p^*, p^*)$$

$$\left|\frac{(h_2^w, k_2^w, l_2^w)}{(h_3^w, k_3^w, l_3^w)} - (h_{23}, k_{23}, l_{23})\right| \le (p^*, p^*, p^*)$$

$$\left|\frac{(h_3^w, k_3^w, l_3^w)}{(h_3^w, k_3^w, l_3^w)} - (h_{33}, k_{33}, l_{33})\right| \le (p^*, p^*, p^*)$$

$$\sum_{j=1}^{3} R\left(\widetilde{w}_j\right) = 1$$

$$h_j^w \le k_j^w \le l_j^w$$

$$h_j^w \ge 0$$

$$j = 1, 2, 3$$

$$\begin{aligned}
\min\quad & \beta^* \\
s.t.\quad & \left|h_1 - 3.5 * l_3\right| \le p * l_3 \\
& \left|k_1 - 4 * k_3\right| \le p * k_3 \\
& \left|l_1 - 4.5 * h_3\right| \le p * h_3 \\
& \left|h_1 - 2.5 * l_2\right| \le p * l_2 \\
& \left|k_1 - 3 * k_2\right| \le p * k_2 \\
& \left|l_1 - 3.5 * h_2\right| \le p * h_2 \\
& \left|h_2 - 1.5 * l_3\right| \le p * l_3 \\
& \left|k_2 - 2 * k_3\right| \le p * k_3 \\
& \left|l_2 - 2.5 * h_3\right| \le p * h_3 \\
& \frac{1}{6} * h_1 + \frac{1}{6} * 4 * k_1 + \frac{1}{6} * l_1 + \frac{1}{6} * h_2 + \frac{1}{6} * 4 \\
& \quad * k_2 + \frac{1}{6} * l_2 + \frac{1}{6} * h_3 + \frac{1}{6} * 4 * k_3 + \frac{1}{6} * l_3 \\
& = 1 \\
& h_1 \le k_1 \le l_1 \\
& h_2 \le k_2 \le l_2 \\
& h_3 \le k_3 \le l_3 \\
& h_1 > 0; \\
& h_2 > 0; \\
& h_3 > 0; \\
& p \ge 0
\end{aligned} \tag{15}$$

Then, the fuzzy weight of decision-makers is obtained by calculating the above inequality group.

$$\begin{aligned}
\widetilde{w}_1^* &= (0.6125, 0.6125, 0.6458); \\
\widetilde{w}_2^* &= (0.2053, 0.2315, 0.2855) \\
\widetilde{w}_3^* &= (0.1330, 0.1407, 0.1792) \\
\beta^* &= (0.3542, 0.3542, 0.3542)
\end{aligned} \tag{16}$$

Finally, the crisp number of fuzzy weights is computed by (1). Therefore, in the decision-making of M company, d_1 is the most important and d_3 is the least.

$$\begin{aligned}
\widetilde{w}_1^* &= 0.6181; \\
\widetilde{w}_2^* &= 0.2361; \\
\widetilde{w}_3^* &= 0.1458
\end{aligned} \tag{17}$$

Step 4. 'First decision-maker' (d_1) selected C_1, C_2, C_3, C_5 as the index, and 'second decision-maker' (d_2) thinks C_4, C_6, C_7 are the most important criteria. 'Third decision-maker' (d_3) selected indicators covering three aspects of capability: C_2, C_7, C_8.

And the weight vector of three decision-makers are $w^1 = (0.3, 0.2, 0.2, 0.3)$, $w^2 = (0.2, 0.4, 0.4)$, and $w^3 = (0.3, 0.4, 0.3)$. The results of the three decision-makers are shown in Tables 4, 5, and 6.

Step 5. The normalized matrix $DM^{(d)}(\mathbf{Y})^*, d \in K$, is obtained based on the (3).

$$\mathrm{DM}^{(1)}\left(\mathbf{Y}^{(1)}\right)^* = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccc} \quad C_1 \quad & \quad C_2 \quad & \quad C_3 \quad & \quad C_5 \quad \end{array} \\ \begin{bmatrix}
\left(0, \frac{2}{9}, \frac{3}{9}\right) & \left(\frac{0.5}{0.9}, \frac{0.6}{0.9}, \frac{0.7}{0.9}\right) & \left(0, \frac{0.1}{0.7}, \frac{0.2}{0.7}\right) & \left(\frac{1}{7}, \frac{2}{7}, \frac{3}{7}\right) \\
\left(\frac{4}{9}, \frac{6}{9}, \frac{7}{9}\right) & \left(\frac{0.3}{0.9}, \frac{0.4}{0.9}, \frac{0.5}{0.9}\right) & \left(\frac{0.2}{0.7}, \frac{0.3}{0.7}, \frac{0.4}{0.7}\right) & \left(\frac{5}{7}, \frac{6}{7}, 1\right) \\
\left(\frac{2}{9}, \frac{3}{9}, \frac{4}{9}\right) & \left(\frac{0.2}{0.9}, \frac{0.3}{0.9}, \frac{0.4}{0.9}\right) & \left(\frac{0.1}{0.7}, \frac{0.2}{0.7}, \frac{0.3}{0.7}\right) & \left(\frac{3}{7}, \frac{4}{7}, \frac{5}{7}\right) \\
\left(\frac{7}{9}, \frac{8}{9}, 1\right) & \left(\frac{0.7}{0.9}, \frac{0.8}{0.9}, \frac{0.9}{0.9}\right) & \left(\frac{0.4}{0.7}, \frac{0.5}{0.7}, \frac{0.7}{0.7}\right) & \left(\frac{4}{7}, \frac{5}{7}, \frac{6}{7}\right)
\end{bmatrix} \end{array}$$

Table 4: Decision matrix of the first decision-maker (d_1).

Alternatives	C_1	C_2	C_3	C_5
A_1	$(0, 2, 3)$	$(0.5, 0.6, 0.7)$	$(0, 0.1, 0.2)$	$(1, 2, 3)$
A_2	$(4, 6, 7)$	$(0.3, 0.4, 0.5)$	$(0.2, 0.3, 0.4)$	$(5, 6, 7)$
A_3	$(2, 3, 4)$	$(0.2, 0.3, 0.4)$	$(0.1, 0.2, 0.3)$	$(3, 4, 5)$
A_4	$(7, 8, 9)$	$(0.7, 0.8, 0.9)$	$(0.4, 0.5, 0.7)$	$(4, 5, 6)$

Table 5: Decision matrix of the second decision-maker (d_2).

Alternatives	C_4	C_6	C_7
A_1	$(1, 2, 3)$	$(0.3, 0.4, 0.5)$	$(5, 6, 7)$
A_2	$(3, 4, 5)$	$(0.1, 0.2, 0.3)$	$(4, 5, 6)$
A_3	$(2, 3, 4)$	$(0, 0.1, 0.2)$	$(7, 8, 9)$
A_4	$(6, 7, 8)$	$(0.7, 0.8, 0.9)$	$(3, 4, 5)$

Table 6: Decision matrix of the third decision-maker (d_3).

Alternatives	C_2	C_7	C_8
A_1	$(0.1, 0.2, 0.3)$	$(4, 5, 6)$	$(0, 1, 2)$
A_2	$(0.3, 0.4, 0.5)$	$(3, 4, 5)$	$(4, 5, 6)$
A_3	$(0.2, 0.3, 0.4)$	$(4, 5, 6)$	$(4, 5, 6)$
A_4	$(0.5, 0.6, 0.7)$	$(2, 3, 4)$	$(3, 4, 5)$

$$\mathrm{DM}^{(2)}\left(\mathbf{Y}^{(2)}\right)^{*} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{ccc} C_4 & C_6 & C_7 \end{array} \\ \begin{bmatrix} \left(\frac{1}{8}, \frac{2}{8}, \frac{3}{8}\right) & \left(\frac{0.3}{0.9}, \frac{0.4}{0.9}, \frac{0.5}{0.9}\right) & \left(\frac{5}{9}, \frac{6}{9}, \frac{7}{9}\right) \\ \left(\frac{3}{8}, \frac{4}{8}, \frac{5}{8}\right) & \left(\frac{0.1}{0.9}, \frac{0.2}{0.9}, \frac{0.3}{0.9}\right) & \left(\frac{4}{9}, \frac{5}{9}, \frac{6}{9}\right) \\ \left(\frac{2}{8}, \frac{3}{8}, \frac{4}{8}\right) & \left(0, \frac{0.1}{0.9}, \frac{0.2}{0.9}\right) & \left(\frac{7}{9}, \frac{8}{9}, 1\right) \\ \left(\frac{6}{8}, \frac{7}{8}, \frac{8}{8}\right) & \left(\frac{0.7}{0.9}, \frac{0.8}{0.9}, \frac{0.9}{0.9}\right) & \left(\frac{3}{9}, \frac{4}{9}, \frac{5}{9}\right) \end{bmatrix} \end{array}$$

$$\mathrm{DM}^{(3)}\left(\mathbf{Y}^{(3)}\right)^{*} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{ccc} C_2 & C_7 & C_8 \end{array} \\ \begin{bmatrix} \left(\frac{0.1}{0.7}, \frac{0.2}{0.7}, \frac{0.3}{0.7}\right) & \left(\frac{4}{6}, \frac{5}{6}, 1\right) & \left(0, \frac{1}{6}, \frac{2}{6}\right) \\ \left(\frac{0.3}{0.7}, \frac{0.4}{0.7}, \frac{0.5}{0.7}\right) & \left(\frac{3}{6}, \frac{4}{6}, \frac{5}{6}\right) & \left(\frac{4}{6}, \frac{5}{6}, 1\right) \\ \left(\frac{0.2}{0.7}, \frac{0.3}{0.7}, \frac{0.4}{0.7}\right) & \left(\frac{4}{6}, \frac{5}{6}, 1\right) & \left(\frac{4}{6}, \frac{5}{6}, 1\right) \\ \left(\frac{0.5}{0.7}, \frac{0.6}{0.7}, 1\right) & \left(\frac{2}{6}, \frac{3}{6}, \frac{4}{6}\right) & \left(\frac{3}{6}, \frac{4}{6}, \frac{5}{6}\right) \end{bmatrix} \end{array} \tag{18}$$

Step 6. According to the above $DM^{(d)}(\mathbf{Y})^{*}, d \in K$, we select $r_j^{(d)+}(\mathbf{Y})$ and $r_j^{(d)-}(\mathbf{Y})$ by (9) and (10).

$$\begin{aligned} & r_j^{(1)+}(\mathbf{Y}) \\ & = \left[\left(\frac{7}{9}, \frac{8}{9}, 1\right) \left(\frac{0.7}{0.9}, \frac{0.8}{0.9}, \frac{0.9}{0.9}\right) \left(\frac{0.4}{0.7}, \frac{0.5}{0.7}, \frac{0.7}{0.7}\right) \left(\frac{5}{7}, \frac{6}{7}, 1\right)\right] \\ & r_j^{(1)-}(\mathbf{Y}) \\ & = \left[\left(0, \frac{2}{9}, \frac{3}{9}\right) \left(\frac{0.2}{0.9}, \frac{0.3}{0.9}, \frac{0.4}{0.9}\right) \left(0, \frac{0.1}{0.7}, \frac{0.2}{0.7}\right) \left(\frac{1}{7}, \frac{2}{7}, \frac{3}{7}\right)\right] \end{aligned}$$

$$\begin{aligned} r_j^{(2)+}(\mathbf{Y}) &= \left[\left(\frac{6}{8}, \frac{7}{8}, \frac{8}{8}\right) \left(\frac{0.7}{0.9}, \frac{0.8}{0.9}, \frac{0.9}{0.9}\right) \left(\frac{7}{9}, \frac{8}{9}, 1\right)\right] \\ r_j^{(2)-}(\mathbf{Y}) &= \left[\left(\frac{1}{8}, \frac{2}{8}, \frac{3}{8}\right) \left(0, \frac{0.1}{0.9}, \frac{0.2}{0.9}\right) \left(\frac{3}{9}, \frac{4}{9}, \frac{5}{9}\right)\right] \\ r_j^{(3)+}(\mathbf{Y}) &= \left[\left(\frac{0.5}{0.7}, \frac{0.6}{0.7}, 1\right) \left(\frac{4}{6}, \frac{5}{6}, 1\right) \left(\frac{4}{6}, \frac{5}{6}, 1\right)\right] \\ r_j^{(3)-}(\mathbf{Y}) &= \left[\left(\frac{0.1}{0.7}, \frac{0.2}{0.7}, \frac{0.3}{0.7}\right) \left(\frac{2}{6}, \frac{3}{6}, \frac{4}{6}\right) \left(0, \frac{1}{6}, \frac{2}{6}\right)\right] \end{aligned} \tag{19}$$

Table 7: Simulated separation measures and closeness coefficients.

	A_1	A_2	A_3	A_4
$S^+(\mathbf{y})$	0.279	0.171	0.244	0.09
$S^-(\mathbf{y})$	0.098	0.192	0.183	0.168
$CC(\mathbf{y})$	0.26	0.53	0.43	0.65

Step 7. Based on the data obtained from the above steps, we calculate the value of $S_i^+(\mathbf{Y}), S_i^-(\mathbf{Y})$ and CC_i in Table 7.

Step 8. If there are underlying factors in the decision matrix, the method using random variable will lead to different choices of final alternative. When there is random variable in the decision matrix, rank the alternatives using degree of dominance. If not, the larger the C_i, the better the alternative $\mathbf{A} = (A_1, A_2, \cdots, A_m)$.

According to Table 7, the rank order of the alternatives is $A_4 > A_2 > A_3 > A_1$.

6.2. Discussion. In this section, we discuss the advantages of the proposed method compared with the existing supplier selection methods. The specific advantages are embodied in the following three ways.

(1) The evaluation results are more objective. GMo-RTOPSIS method makes up for many shortcomings of traditional TOPSIS. GMo-RTOPSIS can process independent decision-making information of multiple decision-makers at the same time, so that the decision-making results are closer to the thought of decision-makers. Moreover, the decision matrix contains different types of information. When describing criteria, the language of decision-makers can be more clearly expressed.

(2) The weight calculation method has been improved. BWM and AHP are similar weight calculation methods, but BWM greatly simplifies the process of comparisons, and the results are more convenient for consistency checking. Traditional BWM has limitations in dealing with information types. Fuzzy BWM can solve the problem of weights in uncertain environments, and the final weights are more realistic.

(3) The fuzzy BWM in the above cases can also be used to determine attribute weights for decision-makers.

7. Conclusion

Under the environment of globalization, choosing the right resilient supplier is an important part of supply chain management. This paper presents a supplier selection model based on the combination of fuzzy BWM and GMo-RTOPSIS. Firstly, the weights of decision-makers are obtained based on fuzzy BWM. Secondly, GMo-RTOPSIS model is used to process the independent decision matrix provided by decision-makers, and alternatives are ranked to select the optimal scheme.

This paper contributes to the existing research from background and method. (1) In the research background of other research, more attention has been paid to supplier selection in static environment or to increasing resilience by improving supply chain. This paper focuses on supplier selection in resilient supply chain under global environment because globalization makes supply chain in dynamic environment and requires the ability to deal with disruptions immediately. Then, according to the relevant research [1, 76], a comprehensive index of resilient supplier selection under dynamic environment is proposed. (2) In terms of research methods, a hybrid multiattribute group decision-making method is proposed by combining fuzzy BWM and GMo-RTOPSIS. This method can effectively reduce the fuzziness, uncertainty, and subjectivity in the decision-making process and restore the decision-maker's thought as much as possible. The method of determining weights is improved. Fuzzy BWM can get more accurate weights by fewer comparisons. Finally, the combination of triangular fuzzy numbers and GMo-RTOPSIS can deal with the evaluation information of independent decision-making of multiple decision-makers in dynamic environment. In the process of weight determination and alternatives evaluation, the data are closer to the decision-maker's idea and the decision-making process is more scientific.

In addition, this paper expands the research methods of multiattribute group decision-making from two aspects. (1) It makes full use of the professional knowledge of decision-makers and expresses their ideas more accurately. In the process of determining the weights of decision-makers, triangular fuzzy numbers are introduced to obtain more objective decision-maker weights. (2) Hybrid research methods are universal. This research method is suitable for supplier selection and other multiattribute group decision-making problems, such as supplier segmentation, performance evaluation, and risk assessment.

Although with the valid study result, there is work remaining to be done in the future. First, this work only focuses on the acquisition of the weights of decision-makers, and future work should focus more on the determination of attributes weights. Second, future work should use empirical data to further testify the reasonability and scientificity of the proposed method. Finally, future work should be developed to support other language sets as rough sets, vague sets, and so on.

Data Availability

The data used to support the findings of this study are available within the paper.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was supported by the National Natural Science Foundation Council of China under Projects nos. 71663055, 71862035, and 71502159; the Foundation of Philosophy and Social Sciences of Yunnan, Project no. YB2017015; and the Applied Basic Research Science Foundation of Yunnan Provincial Department of Science and Technology under Project no. 2015FD028.

References

[1] A. Amindoust, "A resilient-sustainable based supplier selection model using a hybrid intelligent method," *Computers & Industrial Engineering*, vol. 126, pp. 122–135, 2018.

[2] A. Chavooshi, A. A. Bahmani, A. Darijani, A. Mootab Saei, E. Mehrabi, and M. Gholipour, "The role of wood and paper industries management of Iran in sustainable development," *Journal of Conservation and Utilization of Natural Resources*, vol. 1, pp. 79–95, 2012.

[3] F. Sabouhi, M. S. Pishvaee, and M. S. Jabalameli, "Resilient supply chain design under operational and disruption risks considering quantity discount: A case study of pharmaceutical supply chain," *Computers & Industrial Engineering*, vol. 126, pp. 657–672, 2018.

[4] R. Rajesh and V. Ravi, "Supplier selection in resilient supply chains: a grey relational analysis approach," *Journal of Cleaner Production*, vol. 86, no. 15, pp. 343–359, 2015.

[5] S. Valipour Parkouhi and A. Safaei Ghadikolaei, "A resilience approach for supplier selection: using fuzzy analytic network process and grey VIKOR techniques," *Journal of Cleaner Production*, vol. 161, pp. 431–451, 2017.

[6] C. S. Holling, "Resilience and stability of ecological systems," *Annual Review of Ecology, Evolution, and Systematics*, vol. 4, no. 1, pp. 1–23, 1973.

[7] Y. Yang and X. Xu, "Post-disaster grain supply chain resilience with government aid," *Transportation Research Part E: Logistics and Transportation Review*, vol. 76, pp. 139–159, 2015.

[8] S. A. Torabi, M. Baghersad, and S. A. Mansouri, "Resilient supplier selection and order allocation under operational and disruption risks," *Transportation Research Part E: Logistics and Transportation Review*, vol. 79, pp. 22–48, 2015.

[9] S. Y. Ponomarov and M. C. Holcomb, "Understanding the concept of supply chain resilience," *The International Journal of Logistics Management*, vol. 20, no. 1, pp. 124–143, 2009.

[10] U. Jüttner and S. Maklan, "Supply chain resilience in the global financial crisis: An empirical study," *Supply Chain Management Review*, vol. 16, no. 4, pp. 246–259, 2011.

[11] T. Papadopoulos, A. Gunasekaran, R. Dubey, N. Altay, S. J. Childe, and S. Fosso-Wamba, "The role of Big Data in explaining disaster resilience in supply chains for sustainability," *Journal of Cleaner Production*, vol. 142, pp. 1108–1118, 2017.

[12] R. Rajesh, "Technological capabilities and supply chain resilience of firms: a relational analysis using total interpretive structural modeling (TISM)," *Technological Forecasting & Social Change*, vol. 118, pp. 161–169, 2017.

[13] A. Haldar, A. Ray, D. Banerjee, and S. Ghosh, "Resilient supplier selection under a fuzzy environment," *International Journal of Management Science and Engineering Management*, vol. 9, no. 2, pp. 147–156, 2014.

[14] D. Pramanik, A. Haldar, S. C. Mondal, S. K. Naskar, and A. Ray, "Resilient supplier selection using AHP-TOPSIS-QFD under a fuzzy environment," *International Journal of Management Science and Engineering Management*, vol. 12, no. 1, pp. 45–54, 2016.

[15] I. I. Mitroff and M. C. Alpaslan, "Preparing for evil," *Harvard Business Review*, vol. 81, no. 4, pp. 105–119, 2003.

[16] H. Peck and M. Christopher, "Building the resilient supply chain," *The International Journal of Logistics Management*, vol. 15, no. 2, pp. 1–14, 2004.

[17] B. Allenby and J. Fink, "Social and ecological resilience: Toward inherently secure and resilient societies," *Science*, vol. 24, pp. 347–364, 2000.

[18] A. L. Pregenzer, "Systems resilience: a new analytical framework for nuclear nonproliferation," Office of Scientific & Technical Information, 2011.

[19] Y. Y. Haimes, "On the definition of resilience in systems," *Risk Analysis*, vol. 29, no. 4, pp. 498–501, 2009.

[20] M. Christopher and H. Peck, "Building the resilient supply chain," *The International Journal of Logistics Management*, vol. 15, no. 2, pp. 1–14, 2004.

[21] P. Mensah and Y. Merkuryev, "Developing a resilient supply chain," *Procedia - Social and Behavioral Sciences*, vol. 110, pp. 309–319, 2014.

[22] M. C. Holcomb and S. Y. Ponomarov, "Understanding the concept of supply chain resilience," *The International Journal of Logistics Management*, vol. 20, pp. 124–143, 2009.

[23] S. Maklan and U. Jüttner, "Supply chain resilience in the global financial crisis: An empirical study," *Supply Chain Management Review*, vol. 16, no. 4, pp. 246–259, 2011.

[24] S. Hosseini, K. Barker, and J. E. Ramirez-Marquez, "A review of definitions and measures of system resilience," *Reliability Engineering & System Safety*, vol. 145, pp. 47–61, 2016.

[25] R. Kumar, S. S. Padhi, and A. Sarkar, "Supplier selection of an Indian heavy locomotive manufacturer: an integrated approach using taguchi loss function, TOPSIS, and AHP," *IIMB Management Review*, 2018.

[26] G. Büyüközkan and S. Güleryüz, "A new integrated intuitionistic fuzzy group decision making approach for product development partner selection," *Computers & Industrial Engineering*, vol. 102, pp. 383–395, 2016.

[27] J. S. Baek, A. Meroni, and E. Manzini, "A socio-technical approach to design for community resilience: A framework for analysis and design goal forming," *Design Studies*, vol. 40, pp. 60–84, 2015.

[28] P. Tamvakis and Y. Xenidis, "Resilience in transportation systems," *Procedia - Social and Behavioral Sciences*, vol. 48, pp. 3441–3450, 2012.

[29] E. D. Vugrin, D. E. Warren, and M. A. Ehlen, "A resilience assessment framework for infrastructure and economic systems: Quantitative and qualitative resilience analysis of petrochemical supply chains to a hurricane," *Process Safety Progress*, vol. 30, no. 3, pp. 280–290, 2011.

[30] S. Hosseini, A. Al Khaled, and M. D. Sarder, "A general framework for assessing system resilience using Bayesian networks: A case study of sulfuric acid manufacturer," *Journal of Manufacturing Systems*, vol. 41, pp. 211–227, 2016.

[31] S. Hosseini and K. Barker, "A Bayesian network model for resilience-based supplier selection," *International Journal of Production Economics*, vol. 180, pp. 68–87, 2016.

[32] S. Hosseini and K. Barker, "Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports," *Computers & Industrial Engineering*, vol. 93, pp. 252–266, 2016.

[33] B. M. Dos Santos, L. P. Godoy, and L. M. S. Campos, "Performance evaluation of green suppliers using entropy-TOPSIS-F," *Journal of Cleaner Production*, vol. 207, pp. 498–509, 2019.

[34] A. Memari, A. Dargi, M. R. Akbari Jokar, R. Ahmad, and A. R. Abdul Rahim, "Sustainable supplier selection: A multi-criteria intuitionistic fuzzy TOPSIS method," *Journal of Manufacturing Systems*, vol. 50, p. 24, 2019.

[35] C. Yu, Y. Shao, K. Wang, and L. Zhang, "A group decision making sustainable supplier selection approach using extended TOPSIS under interval-valued Pythagorean fuzzy environment," *Expert Systems with Applications*, vol. 121, pp. 1–17, 2019.

[36] Z. Chen and W. Yang, "An MAGDM based on constrained FAHP and FTOPSIS and its application to supplier selection," *Mathematical and Computer Modelling*, vol. 54, no. 11-12, pp. 2802–2815, 2011.

[37] A. Dargi, A. Anjomshoae, M. R. Galankashi, A. Memari, and M. B. M. Tap, "Supplier selection: A fuzzy-ANP approach," in *Proceedings of the 2nd International Conference on Information Technology and Quanttative Management, (ITQM '14)*, vol. 31, pp. 691–700, Russia, June 2014.

[38] S. K. Jauhar and M. Pant, "Integrating DEA with DE and MODE for sustainable supplier selection," *Journal of Computational Science*, vol. 21, pp. 299–306, 2017.

[39] I. Dobos and G. Vörösmarty, "Inventory-related costs in green supplier selection problems with data envelopment analysis (DEA)," *International Journal of Production Economics*, 2018.

[40] K. Rashidi and K. Cullinane, "A comparison of fuzzy DEA and fuzzy TOPSIS in sustainable supplier selection: Implications for sourcing strategy," *Expert Systems with Applications*, vol. 121, pp. 266–281, 2019.

[41] Y. Wu, K. Chen, B. Zeng, H. Xu, and Y. Yang, "Supplier selection in nuclear power industry with extended VIKOR method under linguistic information," *Applied Soft Computing*, vol. 48, pp. 444–457, 2016.

[42] A. Awasthi, K. Govindan, and S. Gold, "Multi-tier sustainable global supplier selection using a fuzzy AHP-VIKOR based approach," *International Journal of Production Economics*, vol. 195, pp. 106–117, 2018.

[43] J. Rezaei, J. Wang, and L. Tavasszy, "Linking supplier development to supplier segmentation using Best Worst Method," *Expert Systems with Applications*, vol. 42, no. 23, pp. 9152–9164, 2015.

[44] H. Gupta and M. K. Barua, "Supplier selection among SMEs on the basis of their green innovation ability using BWM and fuzzy TOPSIS," *Journal of Cleaner Production*, vol. 152, pp. 242–258, 2017.

[45] J. Rezaei, "Best-worst multi-criteria decision-making method," *Omega* , vol. 53, pp. 49–57, 2015.

[46] J. Rezaei, "Best-worst multi-criteria decision-making method: some properties and a linear model," *Omega* , vol. 64, pp. 126–130, 2016.

[47] Z.-P. Tian, J.-Q. Wang, and H.-Y. Zhang, "An integrated approach for failure mode and effects analysis based on fuzzy best-worst, relative entropy, and VIKOR methods," *Applied Soft Computing*, vol. 72, pp. 636–646, 2018.

[48] S. Guo and H. Zhao, "Fuzzy best-worst multi-criteria decision-making method and its applications," *Knowledge-Based Systems*, vol. 121, pp. 23–31, 2017.

[49] A. Hafezalkotob and A. Hafezalkotob, "A novel approach for combination of individual and group decisions based on fuzzy best-worst method," *Applied Soft Computing*, vol. 59, pp. 316–325, 2017.

[50] Z.-P. Tian, J.-Q. Wang, J. Wang, and H.-Y. Zhang, "A multiphase QFD-based hybrid fuzzy MCDM approach for performance evaluation: A case of smart bike-sharing programs in Changsha," *Journal of Cleaner Production*, vol. 171, pp. 1068–1083, 2018.

[51] J. Rezaei, O. Kothadiya, L. Tavasszy, and M. Kroesen, "Quality assessment of airline baggage handling systems using SERVQUAL and BWM," *Tourism Management*, vol. 66, pp. 85–93, 2018.

[52] F. Nawaz, M. R. Asadabadi, N. K. Janjua, O. K. Hussain, E. Chang, and M. Saberi, "An MCDM method for cloud service selection using a Markov chain and the best-worst method," *Knowledge-Based Systems*, vol. 159, pp. 120–131, 2018.

[53] G. Van de Kaa, M. Janssen, and J. Rezaei, "Standards battles for business-to-government data exchange: Identifying success factors for standard dominance using the best worst method," *Technological Forecasting & Social Change*, vol. 137, pp. 182–189, 2018.

[54] P. Shojaei, S. A. Seyed Haeri, and S. Mohammadi, "Airports evaluation and ranking model using Taguchi loss function, best-worst method and VIKOR technique," *Journal of Air Transport Management*, vol. 68, pp. 4–13, 2018.

[55] N. Salimi and J. Rezaei, "Evaluating firms' R&D performance using best worst method," *Evaluation and Program Planning*, vol. 66, pp. 147–155, 2018.

[56] J. Ren, H. Liang, and F. T. S. Chan, "Urban sewage sludge, sustainability, and transition for Eco-City: Multi-criteria sustainability assessment of technologies based on best-worst method," *Technological Forecasting & Social Change*, vol. 116, pp. 29–39, 2017.

[57] C.-L. Hwang and K. Yoon, *Multiple Attributes Decision Making: Methods and Applications*, New York, NY, USA, 1981.

[58] G. R. Jahanshahloo, F. Hosseinzadeh Lotfi, and A. R. Davoodi, "Extension of TOPSIS for decision-making problems with interval data: interval efficiency," *Mathematical and Computer Modelling*, vol. 49, no. 5-6, pp. 1137–1142, 2009.

[59] Z. Yue, "An extended TOPSIS for determining weights of decision makers with interval numbers," *Knowledge-Based Systems*, vol. 24, no. 1, pp. 146–153, 2011.

[60] L. Dymova, P. Sevastjanov, and A. Tikhonenko, "A direct interval extension of TOPSIS method," *Expert Systems with Applications*, vol. 40, no. 12, pp. 4841–4847, 2013.

[61] C. Chen, "Extensions of the TOPSIS for group decision-making under fuzzy environment," *Fuzzy Sets and Systems*, vol. 114, no. 1, pp. 1–9, 2000.

[62] R. A. Krohling and V. C. Campanharo, "Fuzzy TOPSIS for group decision making: a case study for accidents with oil spill in the sea," *Expert Systems with Applications*, vol. 38, no. 4, pp. 4190–4197, 2011.

[63] G. Lee, K. S. Jun, and E.-S. Chung, "Robust spatial flood vulnerability assessment for Han River using fuzzy TOPSIS with α-cut level set," *Expert Systems with Applications*, vol. 41, no. 2, pp. 644–654, 2014.

[64] F. E. Boran, S. Genç, M. Kurt, and D. Akay, "A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method," *Expert Systems with Applications*, vol. 36, no. 8, pp. 11363–11368, 2009.

[65] H. Shih, H. Shyur, and E. S. Lee, "An extension of TOPSIS for group decision making," *Mathematical and Computer Modelling*, vol. 45, no. 7-8, pp. 801–813, 2007.

[66] D.-F. Li, Z.-G. Huang, and G.-H. Chen, "A systematic approach to heterogeneous multiattribute group decision making," *Computers & Industrial Engineering*, vol. 59, pp. 561–572, 2010.

[67] B. Vahdani, S. M. Mousavi, and R. Tavakkoli-Moghaddam, "Group decision making based on novel fuzzy modified TOPSIS method," *Applied Mathematical Modelling*, vol. 35, no. 9, pp. 4257–4269, 2011.

[68] R. Lourenzutti and R. A. Krohling, "A generalized TOPSIS method for group decision making with heterogeneous information in a dynamic environment," *Information Sciences*, vol. 330, pp. 1–18, 2016.

[69] S. H. Zanakis, A. Solomon, N. Wishart, and S. Dublish, "Multi-attribute decision making: a simulation comparison of select methods," *European Journal of Operational Research*, vol. 107, no. 3, pp. 507–529, 1998.

[70] A.-H. Peng and X.-M. Xiao, "Material selection using PROMETHEE combined with analytic network process under hybrid environment," *Materials and Corrosion*, vol. 47, pp. 643–652, 2013.

[71] X. Sun, V. Gollnick, Y. Li, and E. Stumpf, "Intelligent multi-criteria decision support system for systems design," *Journal of Aircraft*, vol. 51, pp. 216–225, 2014.

[72] S. H. Mousavi-Nasab and A. Sotoudeh-Anvari, "A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems," *Materials and Corrosion*, vol. 121, pp. 237–253, 2017.

[73] I. Eusgeld, W. Kröger, G. Sansavini, M. Schläpfer, and E. Zio, "The role of network theory and object-oriented modeling within a framework for the vulnerability analysis of critical infrastructures," *Reliability Engineering & System Safety*, vol. 94, no. 5, pp. 954–963, 2009.

[74] J. Johansson and H. Hassel, "An approach for modelling interdependent infrastructures in the context of vulnerability analysis," *Reliability Engineering & System Safety*, vol. 95, no. 12, pp. 1335–1344, 2010.

[75] J. Johansson, H. Hassel, and E. Zio, "Reliability and vulnerability analyses of critical infrastructures: Comparing two approaches in the context of power systems," *Reliability Engineering & System Safety*, vol. 120, pp. 27–38, 2013.

[76] S. Hosseini and A. A. Khaled, "A hybrid ensemble and AHP approach for resilient supplier selection," *Journal of Intelligent Manufacturing*, pp. 1–22, 2016.

[77] D. D. Wu, Y. Zhang, and D. L. Olson, "Fuzzy multi-objective programming for supplier selection and risk modeling: a possibility approach," *European Journal of Operational Research*, vol. 200, no. 3, pp. 774–787, 2010.

[78] M. Christopher, *Logistics and Supply Chain Management*, Financial Times/Prentice Hall, 2010.

[79] M. Mellat-Parast, "Developing a resilient supply chain through supplier flexibility and reliability assessment," *International Journal of Production Research*, vol. 54, no. 1, pp. 302–321, 2016.

[80] R. Reyes Levalle and S. Y. Nof, "Resilience by teaming in supply network formation and re-configuration," *International Journal of Production Economics*, vol. 160, pp. 80–93, 2015.

[81] J. Töyli, A. Wieland, and C. M. Wallenburg, "The influence of relational competencies on supply chain resilience: a relational view," *International Journal of Physical Distribution Logistics Management*, vol. 43, pp. 300–320, 2013.

[82] S. K. Mahapatra, R. Narasimhan, and P. Barbieri, "Strategic interdependence, governance effectiveness and supplier performance: A dyadic case study investigation and theory development," *Journal of Operations Management*, vol. 28, no. 6, pp. 537–552, 2010.

[83] L. A. Zadeh, "Fuzzy sets," *Information and Computation*, vol. 8, pp. 338–353, 1965.

[84] S. H. Chen and C. H. Hsieh, "Representation, ranking, distance, and similarity of L-R type fuzzy number and application," *Australian Journal of Intelligent Processing Systems*, vol. 6, pp. 217–229, 2000.

[85] H. Zhao and S. Guo, "Selecting green supplier of thermal power equipment by using a hybrid MCDM method for sustainability," *Sustainability*, vol. 6, no. 1, pp. 217–235, 2014.

[86] M. Dağdeviren, S. Yavuz, and N. Kilinç, "Weapon selection using the AHP and TOPSIS methods under fuzzy environment," *Expert Systems with Applications*, vol. 36, no. 4, pp. 8143–8151, 2009.

[87] F. A. Lootsma, "Saaty's priority theory and the nomination of a senior professor in operations Research," *European Journal of Operational Research*, vol. 4, no. 6, pp. 380–388, 1980.

[88] C. L. Hwang and K. P. Yoon, *Multiple Attributes Decision Making: Methods and Applications*, 1981.