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Research Article

Innovative Multi-Criteria Decision-Making Approach for Supplier Evaluation: Combining TLF, Fuzzy BWM, and VIKOR

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ABSTRACT

Addressing the performance issues of underperforming suppliers necessitates a thorough evaluation, serving as a catalyst for initiating supplier development efforts. However, the inherent inaccuracies in information introduce complexity, especially when human judgment is involved in the supplier evaluation process. Associated with such problem, this study presents a novel methodology for supplier performance evaluation in the crumb rubber industry, integrating the Taguchi Loss Function (TLF), fuzzy Best-Worst Method (BWM), and VIKOR technique in group decision-making environment. Aimed at addressing the challenges in industries with variable supplier quality and performance, such as the crumb rubber industry in Indonesia, the methodology was empirically tested to demonstrate its practical utility. The process involved identifying evaluation criteria through literature review tailored to the needs of decision makers (DMs), applying TLF to quantify losses from supplier performance deviations, using fuzzy BWM to determine criteria weights based on the DMs judgment, and employing the VIKOR technique for comprehensive supplier ranking. The findings underscore the methodology's effectiveness in enhancing decision-making, offering a unified metric that accommodates diverse criteria and balances precise data with subjective assessments. This approach simplifies the evaluation process, particularly in situations with conflicting interests among decision-makers. Demonstrating its practical application in the crumb rubber industry, the study highlights the methodology's potential for broader industrial applicability. Future research could explore comparative analyses with other analytical methods, further establishing the methodology's robustness and adaptability in different management contexts.

Keywords: supplier evaluation, group decision-making, Taguchi loss function, fuzzy BWM, VIKOR

INTRODUCTION

In the era of globalization, companies face heightened challenges in their supply chain (SC) systems, marked by an increasingly volatile and uncertain market environment. This evolution necessitates a strategic shift in business processes, with a focus on enhancing supply chain performance to maintain competitiveness. As Silvestre (2015) emphasizes, the key to navigating this ever-changing business landscape lies in the implementation of a well-structured and adaptable SC system. Such a system not only needs to be flexible to accommodate rapidly shifting customer demands but also efficient to ensure cost-effectiveness and profit maximization. These dual objectives of flexibility and efficiency in supply chain management have become critical in enabling companies to thrive amidst global market pressures.

Strategic decisions in supply chain management, particularly in purchasing, have a profound impact on overall efficiency and competitiveness [1], [2]. While the literature extensively discusses various methods of supplier evaluation and selection, it often lacks a comprehensive approach that integrates multiple advanced methodologies. This study aims to fill this gap by exploring the combined application of Taguchi Loss Function, the Best-worst Method (BWM), and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), a synergy not extensively examined in previous research. This integration promises to bring a new dimension to supplier evaluation, especially in complex industrial sectors like the crumb rubber industry. In doing so, our research extends the existing frameworks by providing a more nuanced and holistic approach to evaluating suppliers, incorporating both quality and performance metrics in a unique way.

Supplier evaluation and selection are critical phases preceding supplier development. This evaluation is typically initiated when suppliers' performance falls below expectations, necessitating development interventions [3]. The selection phase involves ranking suppliers to determine which ones should be prioritized for development, given the limited resources available for such initiatives. This step is crucial for organizations aiming to maintain strategic competitiveness, as it directly influences profitability [4]. Supplier evaluation presents a complex multi-criteria decision-making (MCDM) challenge. It requires balancing various, often conflicting and uncertain, criteria during the decision-making process. This complexity is heightened as evaluations must consider both qualitative and quantitative criteria, necessitating trade-offs between different suppliers' performances [5]. MCDM problems are broadly categorized into continuous and discrete types [6] with multi-objective decision-making (MODM) methods addressing continuous problems and multi-attribute decision-making (MADM) methods focusing on discrete problems.

The literature on supplier evaluation highlights a range of multi-attribute decision-making (MADM) methods, with AHP (Analytic Hierarchy Process), ANP (Analytic Network Process), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), ELECTRE (ELimination Et Choix Traduisant la REalité), VIKOR, and PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) being among the most prominent [6], [7]. Our paper focuses on these methods, particularly their application in supplier evaluation. AHP and ANP are frequently used for ranking suppliers through pairwise comparisons among evaluation criteria [8], [9], [10]. Recent researches adopted the combined MADM methods in supplier evaluation and selection models to improve decision quality and accuracy. For instance, Jain et al. [11] employed a fuzzy AHP in the automotive industry, while Pitchipoo et al. [12] combined AHP with grey relational analysis in the process industry. These integrated approaches reflect a trend towards more nuanced supplier evaluation models that better address the complexity of modern supply chains. Yadav and Sharma [13] proposed a hybrid approach combining Data Envelopment Analysis (DEA) and AHP and found that DEA-AHP provides an improved decision compare to basic AHP. Liu and Zang [14] proposed a novel integrated approach in supplier evaluation and selection problem using combined methods in which objectives weights are calculated using entropy weight and supplier rank is obtained based on an improved ELECTRE-III procedures. Hsu et al. [15] presented green supplier evaluation and selection model based on their carbon performance and provided a supplier ranking list by utilizing ANP and VIKOR ranking technique. Ho et al. [16] developed an integrated analytical approach to improve the performance of sourcing system by construct methodology employing QFD to accommodate stakeholder requirement into evaluation criteria, and AHP to determine criteria weight and supplier preference with respect to criteria. Lima-Junior and Carpinetti [17] categorized and evaluated suppliers based on their performance on cost and delivery utilizing SCOR® performance metrics and combined two fuzzy TOPSIS models.

Recent advancements in multi-attribute decision-making (MADM) have seen the integration of fuzzy set theory (FST) to better handle uncertainties in input data and human judgment. This evolution, as Banaeian et al. [4] highlighted, represents a significant stride in refining supplier evaluation models. Notable contributions in this domain include Chang et al. [18], who utilized fuzzy DEMATEL for identifying key supplier evaluation criteria, and Parkouhi and Ghadikolaei [19], who developed a hybrid fuzzy ANP and grey-VIKOR approach for the Wood and Paper Industry. Further, Chen et al. [20] and Adali et al. [21] explored fuzzy PROMETHEE methods in group decision-making contexts for supplier evaluation. This trend towards integrating fuzzy logic with established MADM methods, as seen in the works of Kuo et al. [22] Gupta and Barua [23], underscores a growing recognition of the need for more sophisticated, adaptable models in supplier evaluation. These models, which include combinations of fuzzy-AHP, fuzzy TOPSIS, and DEA, as demonstrated by Zeydan et al. [24], aim to provide a more comprehensive, flexible approach to evaluating suppliers, factoring in both quantitative and qualitative criteria. As Büyüközkan and Çifçi [25] and Dalalah et al. [26] further extend this discussion by proposing frameworks that blend fuzzy DEMATEL with ANP and TOPSIS, thus enhancing the decision-making process in the context of green supply chain management and group-based MCDM scenarios.

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The advancement of multi-attribute decision-making (MADM) methods, particularly the integration of these methods with newer approaches, has paved the way for novel decision-making models in supplier evaluation. A noteworthy addition to this repertoire is the Best-worst method (BWM), introduced by Rezai [27] in 2015 and gradually adopted in various studies. For example, Gupta and Barua [23 effectively utilized BWM in conjunction with fuzzy TOPSIS to enhance supplier evaluation in Small and Medium Enterprises (SMEs), focusing on green criteria. Simmilarly, Massomi et al. [28] combined fuzzy BWM with COPRAS (Complex Proportional Assessment of Alternatives) and WASPAS (Weighted Aggregated Sum-Product Assessment) to assess strategic suppliers, particularly in the context of Iran's renewable energy sector. The work of Tavana et al. [29] and Javad et al. [33] [30] further exemplifies the versatility of BWM, integrating it with fuzzy-based methods for practical applications in industries like recycling and steel manufacturing. Notably, Aboutorab et al. [31] and Wu et al. [32] have expanded the scope of BWM by integrating it with Z-numbers and VIKOR technique, respectively, demonstrating its efficacy in managing uncertainties and enhancing group decision-making processes. These studies collectively underscore the growing relevance and applicability of BWM in addressing the complex and dynamic challenges of supplier evaluation.

Upon thorough examination of current supplier evaluation methodologies, it becomes evident that there is an unexplored area in the literature: the integration of Taguchi Loss Function (TLF) with BWM and VIKOR. While numerous studies have ventured into combining various Multiple Attribute Decision-Making (MADM) techniques, the specific amalgamation of TLF, fuzzy BWM, and VIKOR remains untouched. This gap in research presents a significant opportunity to develop a more comprehensive and robust framework for supplier evaluation. The incorporation of Taguchi Loss Function, renowned for its effectiveness in quality engineering, offers a methodical and quantifiable approach to evaluating supplier quality and performance. Our research seeks to bridge this gap, aiming to equip decision-makers with a broader and more nuanced understanding of supplier capabilities. By integrating Taguchi Loss Function for quality assessment, BWM for preference modeling, and VIKOR for establishing compromise rankings among suppliers, this study introduces an innovative decision-making framework in the field of supplier evaluation. Specifically, we apply this novel approach to address the challenges faced in supplier evaluation within the crumb rubber industry, showcasing its potential to transform supplier assessment practices in complex industrial contexts. In this study, we propose supplier evaluation framework that combines

METHODS

Taguchi Loss Function (TLF), fuzzy Best-worst Method (fuzzy BWM), and VIKOR technique. Each of these methods will be briefly explored in the following sub-section, providing insight into their integration and functionality to contribute to the proposed evaluation framework.

Taguchi Loss Function (TLF)

The Taguchi Loss Function (TLF) is a pivotal method in quality engineering, designed to quantify the cost incurred by customers when product quality deviates from its target value. TLF is structured to provide a quantifiable range of acceptable quality, assessing losses based on the deviation of quality characteristics from their desired targets. A key feature of TLF is its use of a quadratic loss function, allowing for a zero loss when quality aligns perfectly with the target value, and escalating losses as quality deviates within predefined specifications. Its versatility is demonstrated by its successful application across diverse fields [33], including healthcare [34]; real estate [35], [36]; airport service quality [37], and manufacturing process [38], [39].

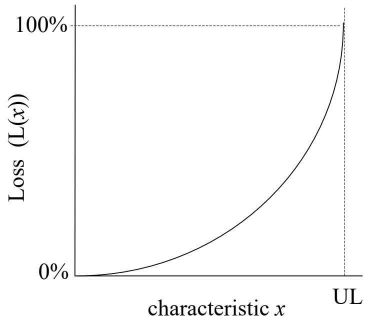
In general, there are two- types of loss functions representing the Taguchi loss, i.e., a one-sided loss function and a two-sided loss function. The first typed function allows one-direction deviation from the target value. Two sub-type of this loss function is referred to as "smaller is better" and "larger is better" as shown in Figure 1(a)-(b). The second type is a two-sided loss function represented by "nominal is best" where the target value is placed at nominal center value Figure 1(c). Assuming $L(x)$ is the loss for specific value of quality characteristic x, m is target value of x and k is a constant factor, then the formulation of $L(x)$for smaller is better" type, "larger is better" type, and "nominal is best" type are given in Equation (1)-(3), respectively.

$$L(x) = \begin{cases} k \times (x)^2 & \text{for single data} \\ k \times \left(\text{MSD} = \frac{1}{n}\sum_{i=1}^{n}(x_i)^2\right) & \text{for } n\text{-data} \end{cases} \quad ; \; k = 100\%/T^2 \tag{1}$$

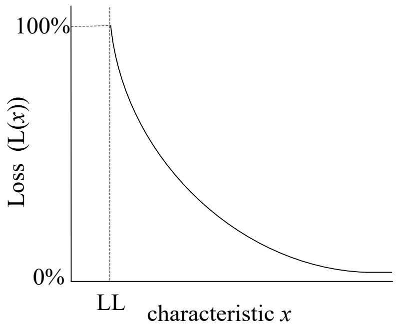
$$L(x) = \begin{cases} k \times \left(\frac{1}{x^2}\right) & \text{for single data} \\ k \times \left(\text{MSD} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{x_i^2}\right)\right) & \text{for } n\text{-data} \end{cases} \quad ; \; k = 100\% \times T^2 \tag{2}$$

$$L(x) = \begin{cases} k \times (x-m)^2 & \text{for single data} \\ k \times \left(\text{MSD} = \frac{1}{n}\sum_{i=1}^{n}(x_i - m)^2\right) & \text{for } n\text{-data} \end{cases} \quad ; \; k = 100\%/T^2 \tag{3}$$

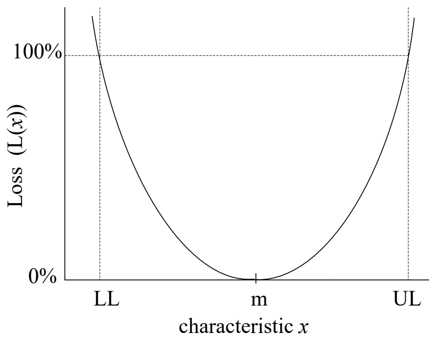
Note that the value of k is determined such that when x reaches tolerance limit (T) set by a decision maker, then $L(x)$ equals 100%. For nominal-is-best loss function, T is the difference between upper and lower limits (UL-LL).



(a). Smaller-is-better



b). Higher-is-better



(c). Nominal-is-best

Figure 1. Type of Taguchi loss function

Fuzzy Best-worst Method (fuzzy BWM)

The Best-worst method (BWM), a recent advancement in multi-attribute decision-making (MADM) introduced by Rezaei [27], utilizes a dual-vector approach for criteria weight calculation This approach involves two vectors: a best-to-others (BtO) vector, comparing the most imprtant criterion against all others, and an others-to-worst *(OtW)* vector, comparing each criterion to the least important one. BWM's efficiency stems from its reduced need for

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comparison data, enhancing the consistency of results over traditional pairwise comparison methods. Its application extends across various domains, including sustainable supply chain [40], [41]; biomass conversion technology [42], airport and airline service quality [37], [43]; risk assessment for business continuity management [44][45]; and supplier selection [46], [47].

Our study incorporates the fuzzy BWM, as Sen and Haorran [48], which leverages linguistic variables over crisp values in criteria comparisons. This integration of fuzzy set theory enhances the method's ability to manage ambiguity in judgment, yielding more reliable weights and consistent performance evaluations.

The steps of fuzzy BWM are described as follow:

1. Define a set of criteria used for evaluation of alternatives as $\{c_1, c_2, ..., c_n\}$ where n is the number of criteria.
2. Determine the best criterion c_B and the worst criterion c_W.
3. Conduct the fuzzy pair-wise comparisons for the best criterion over other criteria using the linguistic terms based on fuzzy intensity scale listed in Table 1. The obtained fuzzy BtO vector is given as $\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots, \tilde{a}_{Bn})$, where $\tilde{a}_{Bj}$ is the fuzzy preference of the best criterion c_B over criterion j; $j = 1, 2, ..., n$; and $\tilde{a}_{BB} = (1,1,1)$.
4. Conduct the fuzzy pair-wise comparisons for other criteria over the worst criterion using the linguistic terms based on fuzzy intensity scale listed in Table 1. The obtained fuzzy BtO vector is given as $\tilde{A}_w = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW})$, where $\tilde{a}_{jW}$ is the fuzzy preference of criterion j over the worst criterion c_W; $j = 1, 2, ..., n$; and $\tilde{a}_{WW} = (1,1,1)$.
5. Compute the optimal fuzzy weights $(\tilde{\omega}_1^*, \tilde{\omega}_2^*, \dots, \tilde{\omega}_n^*)$. The optimal fuzzy weight for each criterion is found when $\tilde{\omega}_B/\tilde{\omega}_j = \tilde{a}_{Bj}$ and $\tilde{\omega}_j/\tilde{\omega}_W = \tilde{a}_{jW}$. This condition can be achieved when the maximum absolute gaps $\left|\tilde{\omega}_B/\tilde{\omega}_j - \tilde{a}_{Bj}\right|$ and $\left|\tilde{\omega}_j/\tilde{\omega}_W - \tilde{a}_{jW}\right|$ for all j are minimized, where $\tilde{\omega}_B, \tilde{\omega}_j, \tilde{\omega}_W, \tilde{a}_{Bj}$, and $\tilde{a}_{jW}$ are triangular fuzzy number and are given as $\tilde{\omega}_B = (l_B^\omega, m_B^\omega, u_B^\omega)$, $\tilde{\omega}_j = (l_j^\omega, m_j^\omega, u_j^\omega)$, $\tilde{\omega}_W = (l_W^\omega, m_W^\omega, u_W^\omega)$, $\tilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$, and $\tilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW})$.

   The mathematical formulation of finding the optimal fuzzy weights can be written as follow:

$$\min \max_j \left\{ \left| \frac{\tilde{\omega}_B}{\tilde{\omega}_j} - \tilde{a}_{Bj} \right|, \left| \frac{\tilde{\omega}_j}{\tilde{\omega}_W} - \tilde{a}_{jW} \right| \right\} \tag{4}$$

s.t.:

$$\sum_{j=1}^{n} R(\tilde{\omega}_j) = 1$$

$$l_j^\omega \le m_j^\omega \le u_j^\omega$$

$$l_j^\omega \ge 0$$

$$j = 1, 2, \dots, n$$

Table 1. Fuzzy intensity of criteria importance

Linguistic Preferences	Fuzzy Preference Number (Triangular Fuzzy Number)
Equal important	(1, 1, 1)
Weakly important	(2/3, 1, 3/2)
Fairly important	(3/2, 2, 5/2)
Very important	(5/2, 3, 7/2)
Absolutely important	(7/2, 4, 9/2)

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Then, the equivalent nonlinearly constrained optimization problem of the Equation (4) is stated as:

$$\min \ \tilde{\varphi} \tag{5}$$

s.t.:

$$\left|\frac{\tilde{\omega}_B}{\tilde{\omega}_j} - \tilde{a}_{Bj}\right| \leq \tilde{\varphi}$$

$$\left|\frac{\tilde{\omega}_j}{\tilde{\omega}_W} - \tilde{a}_{jW}\right| \leq \tilde{\varphi}$$

$$\sum_{j=1}^{n} R(\tilde{\omega}_j) = 1$$

$$l_j^{\omega} \leq m_j^{\omega} \leq u_j^{\omega}$$

$$l_j^{\omega} \geq 0$$

$$j = 1, 2, \dots, n$$

where $\tilde{\varphi} = (l^{\varphi}, m^{\varphi}, u^{\varphi})$.

By assuming $\tilde{\varphi}^* = (k^*, k^*, k^*)$, $k^* \leq l^{\varphi}$, the Equation (5) can be converted to Equation (6) below.

$$\min \ \tilde{\varphi}^* \tag{6}$$

s.t.:

$$\left|\frac{(l_B^{\omega}, m_B^{\omega}, u_B^{\omega})}{(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})} - (l_{Bj}, m_{Bj}, u_{Bj})\right| \leq (k^*, k^*, k^*)$$

$$\left|\frac{(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})}{(l_W^{\omega}, m_W^{\omega}, u_W^{\omega})} - (l_{jW}, m_{jW}, u_{jW})\right| \leq (k^*, k^*, k^*)$$

$$\sum_{j=1}^{n} R(\tilde{\omega}_j) = 1$$

$$l_j^{\omega} \leq m_j^{\omega} \leq u_j^{\omega}$$

$$l_j^{\omega} \geq 0$$

$$j = 1, 2, \dots, n$$

6. Convert the fuzzy weight of criterion to crisp weight using the graded mean integration representation (GMIR) method using Equation (7).

$$R(\tilde{a}_i) = \frac{l_i + 4m_i + u_i}{6} \tag{7}$$

where $\tilde{a}_i = (l_i, m_i, u_i)$ is triangular fuzzy number, and $R(\tilde{a}_i)$ is the GMIR of $\tilde{a}_i$.

VIKOR Technique

VIKOR technique, introduces by Opricovic [49] in 1998, addresses decision-making problems characterized by conflicting criteria where a simultaneous satisfaction of all criteria is often unattainable. Central to VIKOR is its ability to evaluate and rank alternatives, offering compromise solutions that are close to the ideal, aiming to balance the interests of all parties involved. This method is particularly effective in scenarios requiring trade-offs, harmonizing the collective interests of a majority with the specific concerns of minorities or opponents [50]. VIKOR's strategic emphasis on compromise and consensus-building makes it a valuable tool in complex decision-making contexts, especially in supplier evaluation where multiple, often conflicting, criteria must be considered.

The VIKOR procedures are composed of the following steps:

1. Obtain f_{ij}, which represents the value of criterion *i* (*i* =1, 2, ..., *n*) for each decision alternative *j* (*j* = 1, 2, ..., *m*).
2. Compute the best value (positive ideal solution) of criterion, f_i^-, and the worst value (negative ideal solution) of criterion, f_i^+, as follow:

$$f_i^+ = \left[\left(\max_j f_{ij} \,\middle|\, i \in I_B\right), \left(\min_j f_{ij} \,\middle|\, i \in I_C\right)\right] \tag{8}$$

$$f_i^- = \left[\left(\min_j f_{ij} \,\middle|\, i \in I_B\right), \left(\max_j f_{ij} \,\middle|\, i \in I_C\right)\right] \tag{9}$$

   where I_B is a benefit typed criteria set and I_C is a cost typed criteria set.

3. Compute the value of S_j and R_j using the following formulation:

$$S_j = \sum_{i=1}^{n} \frac{\omega_i(|f_i^+ - f_{ij}|)}{(f_i^+ - f_i^-)} \tag{10}$$

$$R_j = \max_i \left(\frac{|f_i^+ - f_{ij}|}{f_i^+ - f_i^-}\right) \tag{11}$$

   where S_j represents the distance of *j*-th alternative from a positive ideal solution, R_j represents the distance of *j*-th alternative from a negative ideal solution, and ω_i denotes criteria weight.

4. A Compute the value of Q_j using the following formulation:

$$Q_j = \frac{v(S_j - S^+)}{S^- - S^+} + \frac{(1-v)(R_j - R^+)}{R^- - R^+} \tag{12}$$

   where $S^+ = \min_j S_j$, $S^- = \max_j S_j$, $R^+ = \min_j R_j$, $R^- = \max_j R_j$, and v indicates the weight which provides a trade-off mechanism between "maximum group utility" and "individual regret". The most frequent used value of this parameter is $v = 0.5$ [51].

5. Rank the alternatives by sorting the values of *S*, *R*, and *Q* in increasing order.
6. Determine a compromise solution(s) as follow:
   Assuming $a^{(1)}$ and $a^{(2)}$ are the first and second-ranked alternative in *Q* list, respectively, then alternative $a^{(1)}$ is the best compromise solution if it satisfies the following conditions.

   Condition 1: Acceptable advantage:

$$Q(a^{(2)}) - Q(a^{(1)}) \geq DQ \tag{13}$$

$$DQ = 1/(m-1) \tag{14}$$

   Condition 2: Acceptable stability in decision-making:
   $a^{(1)}$ is also rank the first according to the value of *S* and/or *R*
   Otherwise, a set of compromised solutions are then derived if one of the above conditions is not satisfied within which the following rules are applied:

   - If the condition 2 is not satisfied, $a^{(1)}$ and $a^{(2)}$ are both the compromised solutions;
   - If the condition 1 is not satisfied, $a^{(1)}$, $a^{(2)}$,..., $a^{(n)}$ become compromised solutions where $a^{(n)}$ is determined by the relation $Q(a^{(n)}) - Q(a^{(1)}) < DQ$ for maximum *n* (the positions of these alternatives are "in closeness").

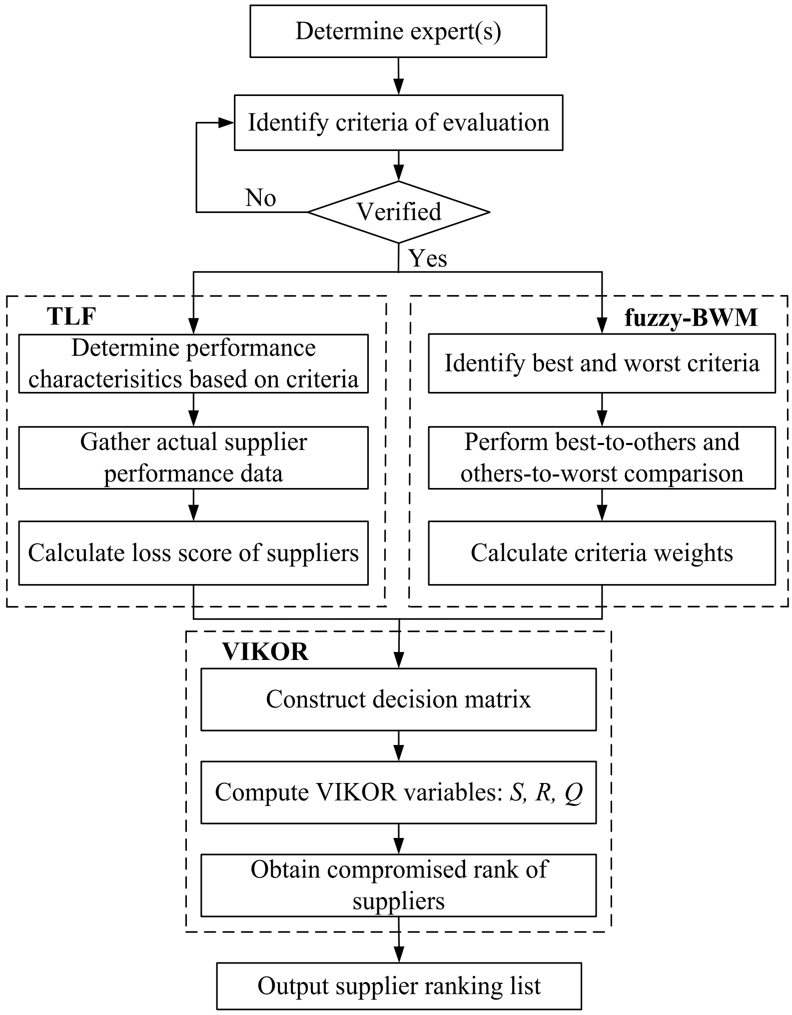

Figure 2. The proposed integrated methodology

The Proposed Evaluation Procedures

The proposed methodology is visually depicted in Figure 2. A systematic summary of the step-by-step evaluation procedures follows, serving as a practical guide to our approach.

Step 1. Determine the candidate of experts for decision making. The number of experts depends on whether the process is conducted through individual decision making, group decision making, or a combination of both.

Step 2. Identify criteria of evaluation. It can be done through a literature review followed by a discussion with the experts. The latter is the process where all identified criteria are screened and validated by the experts to ensure its relevance to the system under consideration.

Step 3. Compute the loss score of suppliers using TLF. Quality characteristics such as target value, T, and k are defined based on a suitable loss function, and loss score of suppliers are then calculated using the corresponding loss function in Equation (1)-(3).

Step 4. Obtain the weight of criteria using fuzzy-BWM. Using experts' opinion, fuzzy weights are calculated using Equation (4-6), and the final crisp weights are obtained using the GMIR method in Equation (7).

Step 5. Obtain the rank of supplier using VIKOR. A maximum and minimum values of loss scores with respect to each criterion are determined using Equation (8)-(9), and the value of S, R, and Q with the predetermined v value are calculated using Equation (10)-(12). Finally, by examining two decision-making conditions of VIKOR, supplier ranking is listed.

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Case Application

To demonstrate the practical utility of our proposed methodology, we conducted a case study within the crumb rubber industry located in Indonesia. The crumb rubber industry, engaged in processing raw rubber into crumb rubber, is classified as an upstream sector. Its products, SIR 20 typed crumb rubber, serve as crucial inputs for downstream industries, including the tire industry and various other rubber-related goods. Notably, Indonesia annually exports approximately 90% of its national crumb rubber production to global markets, encompassing destinations like the United States, Singapore, Japan, China, and several European countries.

The escalating demand and stringent quality standards imposed by customers compel the company to consistently increase production volumes and enhance the quality of crumb rubber. The raw material is replenished from various sources of local rubber smallholders, characterized by limited capacity, unpredictable delivery lead times, and varying quality ranging from low to medium. To prevent potential material shortages, the company secures a daily supply from suppliers at a predetermined fixed price. Owing to the uncertain output quantity in the raw rubber tapping process, the existing policy permits suppliers to deliver raw material at irregular intervals throughout the week. Presently, out of the 18 current suppliers, only 25% consistently adhere to a regular supply schedule on a daily basis. So far, the company lacks formal assessment and evaluation procedures for its suppliers. Following an extensive discussion, the chief executive has decided to embrace a more structured and formalized approach for the supplier evaluation process, making it an excellent testing ground for the application of our proposed research.

Step 1: Determine the experts.

Throughout the data collection process, the opinions of both the Chief (senior decision-maker, DM1) and a panel of middle managers were systematically gathered, tailored to the specific characteristics and requirements of the data. The middle management representatives comprised supervisors from purchasing (DM2), production (DM3), quality control (DM4), and warehousing (DM5). In certain circumstances, the valuable input from the panel, acting as a supportive team through knowledge-sharing and collaborative efforts, proved instrumental in enhancing the Chief's decision accuracy, particularly in situations where he faces a lack of knowledge and experience to make well-informed decisions.

Step 2: Identify the criteria of evaluation.

Without losing generality, the chief conducts an initial screening of suppliers based on their overall performance before proceeding to the evaluation phase. Consequently, five standout candidates are selected to undergo the evaluation process. During this phase, the proposed methodology is systematically applied to the leading five suppliers, considering pertinent criteria. After presenting a preliminary list of criteria, drawn from an extensive literature review, to the panel, five criteria—namely, quality (C1), quantity (C2), continuity (C3), responsiveness (C4), and reputation (C5)—are ultimately identified as the most relevant for supplier evaluation.

Step 3. Compute the loss score of suppliers using TLF.

Considering the nature of the criteria, the panel reached a consensus to employ a "larger-is-better" type loss function to define the performance characteristics of all suppliers. The determination of a target value and tolerance limit for supplier performance with respect to each criterion was appropriately achieved through panel discussions. The outcomes are presented in Table 2.

The explanation of Taguchi parameters for each criterion is as follow:

Quality (C1): This criterion signifies that the dry rubber composition (%DRC) should be a minimum of 46% of raw rubber to meet the quality standards for SIR 20 production. A 100% loss is incurred at the tolerance limit of 46% DRC, diminishing gradually to 0% as the DRC increases to 100%.

Quantity (C2): A zero loss incurs from a supplier whose supply quantity is the largest, and the tolerance limit is down to 30% of this supplier's. It means that the company will incur 100% loss if there are other candidates whose supply quantity falls at this limit.

Table 2. The loss score of suppliers using TLF

Criteria	**Target value**	**Tolerance limit (T, %)**	**Loss at T (%)**	$\boldsymbol{k}$	**Loss Function $\boldsymbol{L(x)}$**
C1	100%	46%	100%	0.212	$L(x)$ = 0.212 MSD
C2	The greatest	30% lower	100%	0.090	$L(x)$ = 0.090 MSD
C3	The most frequent	20% lower	100%	0.040	$L(x)$ = 0.040 MSD
C4	Score of 100	70	100%	4900	$L(x)$ = 4900 $(1/x^2)$
C5	Score of 100	75	100%	5625	$L(x)$ = 5625 $(1/x^2)$

Continuity (C3): This criterion denotes the monthly delivery frequency of raw rubber. The tolerance limit is set at 20% of the frequency committed by the most frequent supplier. Hence, the company experiences a 100% loss if any supplier's delivery frequency reaches the tolerance limit, while the most frequent supplier incurs zero loss.

Responsiveness (C4): This criterion is assessed qualitatively, considering factors like the ability to fulfill expedited or emergency orders, provide quick responses to customer complaints, and manage product returns. The decision-maker conducts a qualitative assessment using a scoring interval of [0, 100]. Zero loss occurs at the highest-rated supplier (score 100), escalating to 100% loss as the rating approaches the tolerance limit of score 70.

Reputation (C5): This criterion reflects suppliers' commitment and integrity in providing their service, encompassing aspects like quality maintenance, prevention of delivery fraudulence, regular maintenance of transportation vehicles, and minimizing odour pollution during transport. Similar to the responsiveness criterion, a qualitative assessment is conducted to rate the supplier's performance using the same scoring interval. A tolerance limit of 75 indicates a 100% loss, with higher scores leading to loss reduction, and a score of 100 resulting in zero loss.

The eight-month performance data of all suppliers regarding quality, quantity, and continuity criteria is presented in Appendix A.1. To finalize the data collection, supplier performance for the responsiveness and reputation criteria is obtained through qualitative assessment. Unlike the data for the first three criteria, aggregate measures for the last two criteria are calculated for the entire period instead of assessing periodically, as the period-by-period performance of each supplier does not exhibit significant variation. The constant factor, k, and loss functions $L(x)$ are determined using the data in Table 2. For instance, as a 100% loss will occur when the monthly supply quantity of a supplier drops 30% lower than the maximum quantity that any suppliers can afford, k is calculated as $k = 100\% \times (30\%)^2 = 0.090$. Additionally, since more than one performance data is collected (as shown in Table 3), the mean squared deviation (MSD) of the data is used to formulate the loss function for the quantity criterion, which is $L(x) = 0.090 \times \text{MSD}$. The values of k and $L(x)$ for the rest of the criteria are calculated in the same manner. Based on the formulated loss function (Table 2), the loss score of each supplier with respect to each criterion is computed, and the results are presented in Table 3.

Step 4. Obtain the weight of criteria using fuzzy-BWM.

The subsequent step in the evaluation process involves the application of fuzzy BWM. Through mutual consensus, the panel selected the best and worst criteria. The preference of the best criterion over all others and the preference of other criteria to the worst criterion are then individually determined by each panel member using the fuzzy intensity scale presented in Table 1. The panel favors the individual rating mechanism to obtain a comparison result from a broader perspective, thereby reducing subjective and biased judgment. Through this process, quality and continuity are identified as the best (most preferred) and worst (least preferred) criteria, respectively. The pairwise comparison results are displayed in Appendix A.2

With the pairwise comparisons in hand, the fuzzy BWM is formulated using Equations (4)-(6). By transforming this problem into an equivalent nonlinearly-constrained optimization problem, five sets of fuzzy weights of criteria in the form of Triangular Fuzzy Numbers (TFN) are calculated, along with the values of $\tilde{\varphi}^*$ (see Appendix A.3). The final crisp weight is then determined using the well-known Geometric Mean of Ideal Ratio (GMIR) method

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Table 3. Decision matrix of loss values

Supplier	C1	C2	C3	C4	C5
S1	66.59	292.43	10.07	60.49	114.80
S2	61.33	17.02	5.30	100.00	87.89
S3	66.02	2052.68	89.57	87.11	100.00
S4	58.54	1414.49	54.16	76.56	69.44
S5	55.06	91285.71	907.80	87.11	100.00

Table 4. Final crisp weights of criteria

Criteria	Mean crisp weights	Individual crisp weights				
		DM1	DM2	DM3	DM4	DM5
C1	0,221	0,235	0,221	0,216	0,218	0,216
C2	0,211	0,214	0,213	0,208	0,219	0,209
C3	0,181	0,179	0,184	0,182	0,178	0,182
C4	0,185	0,186	0,187	0,185	0,181	0,185
C5	0,202	0,185	0,195	0,209	0,211	0,208
φ^*		0,419	0,299	0,299	0,246	0,299

through Equation (7). By averaging those values, the mean crisp weights are obtained, and the results are presented in Table 4. For example, based on the reference rating of the chief (DM1) on quantity criterion, the fuzzy weight is calculated as $\widetilde{\omega}^*_2$ = (0.022, 0.025, 0.027) from which the crisp weight is then calculated using GMIR as $\omega^*_2 =$ [0.022) + (4 * 0.025) + (0.027)]/6 = 0.211.

Given that the preference rating procedure was conducted by multiple Decision Makers (DMs) in this study, a consistency check was performed for all φ^*values, starting from the maximum to the minimum value. The rationale behind this approach is that if the maximum φ^* is found consistent, then the rest of the φ^* values would also exhibit consistency. From Table 8, it is evident that the maximum φ^* in the set is 0.419, with a corresponding value $a_{BW} =$ (7/2, 4, 9/2) and a consistency index of 8.04 (Guo & Zhao, 2017). Therefore, the consistency ratio is calculated as 0.4198 / 8.04 = 0.056, signifying a very high consistency due to its proximity to zero. Given the consistency of the maximum φ^* in this case, it can be inferred that all φ^* values in the set are also consistent.

Step 5: Obtain the rank of supplier using VIKOR.

The VIKOR technique involves using the decision matrix of supplier loss scores (Table 3) and criteria weights (Table 4) as inputs to rank the suppliers. It is important to note that the data in the decision matrix are not presented on the same scale, rendering them less comparable with each other. Therefore, a linear scale transformation is employed to normalize the loss scores for all criteria. In this method, a normalized value of loss score, r_{ij}, as a cost (negative) criterion, is computed as $r_{ij} = x_j^{min} / x_{ij}$, where x_{ij} is the loss score of suppliers i for criteria j and $x_j^{\min} = \min_i x_j$. Consequently, the normalized decision matrix is presented in Table 5.

Table 5. Normalized decision matrix of loss values

Supplier	C1	C2	C3	C4	C5
S1	0,827	0,058	0,526	1,000	0,605
S2	0,898	1,000	1,000	0,605	0,790
S3	0,834	0,008	0,059	0,694	0,694
S4	0,941	0,012	0,098	0,790	1,000
S5	1,000	0,000	0,006	0,694	0,694

Table 6. The value of S, R and Q of suppliers

Supplier *n*	S	S-based rank	R	R-based rank	Q	Q-based rank
S1	0,714	4	0,218	5	0,811	4
S2	0,422	1	0,181	1	0,000	1
S3	0,891	5	0,209	3	0,887	5
S4	0,542	2	0,209	2	0,505	2
S5	0,693	3	0,212	4	0,699	3
	$S^* = 0.422$		$R^* = 0.181$		$j = 5$	
	$S^- = 0.891$		$R^- = 0.218$		DQ = 0.25	

The VIKOR procedures start by calculating the maximum and minimum values (Equation (8)-(9)) for each normalized data concerning each criterion. Subsequently, the values of S_i, R_i, and Q_i are determined using Equation (10)-(12), where the value of v is set to 0.5. As shown in Table 6, supplier 2 and supplier 4 are identified as having the lowest and the second lowest Q, respectively. Upon examining the condition of VIKOR's compromised solution, the criteria of "Acceptable advantage" (Equation (13)) are satisfied, as the value Q(S4) – Q(S2) = 0.5054, which is greater than DQ = 1/(5-1) = 0.25 (Equation 14)). Moreover, it is evident that supplier 2 also holds the minimum values of both S and R. Consequently, it qualifies as a stable alternative, satisfying the second condition of "Acceptable stability in decision-making." Therefore, the conclusive ranking of suppliers can be articulated as follows: S2 > S4 > S8 > S1 > S3, with supplier 2 securing the highest rank, followed by supplier 4, supplier 8, supplier 1, and supplier 3, respectively.

Discussion

This research introduces a comprehensive methodology for compromised multi-criteria decision-making, seamlessly integrating the TLF, fuzzy BWM, and VIKOR in the performance evaluation of suppliers. The application of this methodology in an industrial case, specifically in evaluating and selecting the best supplier in the crumb rubber industry, validates its effectiveness in addressing empirical case problems using real data and expert feedback, whether through single or group opinions. The key advantage of adopting this methodology lies in its ability to leverage the strengths of each individual method concurrently, facilitating decision-making in scenarios with conflicting interests among decision-makers (DMs). These combined methods offer a more structured and efficient decision-making process, utilizing a standardized unit of performance measurement for suppliers. The methodology ensures a compromised decision that aligns with all involved interests. Furthermore, it adeptly handles both crisp data and imprecise human judgment, providing a more effective decision-making process.

For decision-makers, the practical implications of this study are significant. The use of Taguchi's quality loss value as a metric for supplier performance evaluation introduces a common and easily understandable language for decision-making. This approach allows decision-makers to set performance target values and tolerance limits, crucial in supplier evaluation where enterprises may have diverse organizational goals and varying criteria with different acceptable tolerance limits. This flexibility enables decision-makers to conduct precise and comprehensive supplier evaluations tailored to their specific goals. Moreover, the integration of fuzzy BWM in this research streamlines computational efforts in pairwise comparisons, reducing the need for extensive comparison data and iterations compared to conventional methods like Analytic Hierarchy Process (AHP). Fuzzy BWM efficiently computes and objectively reflects the relative importance of each performance criterion, especially in the presence of conflicting criteria and the inherent vagueness in human judgment. By incorporating fuzzy BWM results into the VIKOR technique, decision-makers can derive a compromised supplier ranking that adheres to the principles of "maximum group utility" and "minimum individual regret" of the opposing parties, delivering a solution closest to the ideal. Hence, the proposed methodology enhances the efficiency of the decision-making process, ensuring a well-informed and balanced supplier selection.

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CONCLUSION

This study has successfully developed and applied an integrated methodology for supplier performance evaluation in the crumb rubber industry, combining the Taguchi Loss Function (TLF), fuzzy Best-Worst Method (BWM), and VIKOR technique. The main findings demonstrate the methodology's efficacy in providing a structured and coherent framework for supplier evaluation, effectively balancing the diverse interests of decision-makers (DMs) and efficiently handling both precise data and subjective human judgment. The study concludes that the integration of TLF, fuzzy BWM, and VIKOR offers a significant advancement in supplier performance evaluation. This methodology not only ensures a unified performance measurement unit that reflects all relevant interests but also enhances the decision-making process in terms of efficiency and consistency. The inclusion of fuzzy BWM notably reduces computational efforts in pairwise comparisons, while the VIKOR method aids in deriving balanced supplier rankings suitable for group decision-making scenarios. Practically, this research offers valuable insights for decision-makers in industries similar to crumb rubber production. The methodology's approach to supplier evaluation can be adapted to suit different organizational goals and criteria, making it a versatile tool in diverse business environments. The study's findings are especially pertinent in industries where supplier performance directly impacts product quality and supply chain efficiency, emphasizing the importance of a comprehensive and nuanced evaluation process.

Looking ahead, future research could focus on comparing the effectiveness of this integrated methodology against other analytical methods in various industrial contexts. This would provide further evidence of its applicability and robustness across different management problems. Additionally, exploring adaptations of this methodology to address specific challenges in other sectors could uncover new practical applications and insights, broadening its relevance and impact.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest that could influence the objectivity, integrity, or impartiality of the research presented in this journal. This work is free from any financial, personal, or professional relationships that might have influenced the content or interpretation of the research findings. The authors affirm the commitment to maintaining transparency and ensuring the highest ethical standards in the dissemination of scholarly knowledge.

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Appendix

A.1 Actual performance of the supplier

Criteria	Supplier	Period							
		1	2	3	4	5	6	7	8
C1	S1	56	56	57	56	56	56	57	57
(% DRC)	S2	59	60	58	59	58	59	58	59
	S3	57	57	56	55	57	57	57	57
	S4	60	60	60	60	61	60	60	60
	S5	62	62	61	62	62	62	63	62
C2	S1	551	484	539	489	509	511	475	381
(ton/month)	S2	2144	1961	2147	2323	2149	2757	2736	1261
	S3	247	223	240	132	165	230	206	142
	S4	238	222	237	259	228	227	199	180
	S5	29	21	30	27	36	38	36	20

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A.1 (cont.)

C3 (times/month)	S1	55	50	51	47	52	50	48	40
	S2	69	57	60	62	68	76	77	76
	S3	22	20	21	12	16	20	18	12
	S4	20	21	22	24	21	23	19	19
	S5	5	4	5	4	7	7	7	5

	Suppliers				
Criteria	**S1**	**S2**	**S3**	**S4**	**S5**
C4 (rating 0-100)	90	70	75	80	75
C5 (rating 0-100)	70	80	75	90	65

A.2 Pairwise comparison of criteria

Best criterion:	**The DMs**	**C1**	**C2**	**C3**	**C4**	**C5**
C1	DM1	(1, 1, 1)	(2/3, 1, 3/2)	(7/2, 4, 9/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)
	DM2	(1, 1, 1)	(2/3, 1, 3/2)	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)
	DM3	(1, 1, 1)	(2/3, 1, 3/2)	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(2/3, 1, 3/2)
	DM4	(1, 1, 1)	(3/2, 2, 5/2)	(7/2, 4, 9/2)	(5/2, 3, 7/2)	(2/3, 1, 3/2)
	DM5	(1, 1, 1)	(2/3, 1, 3/2)	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(2/3, 1, 3/2)

Worst criterion: C3	**The DMs**				
	DM1	**DM2**	**DM3**	**DM4**	**DM5**
C1	(7/2, 4, 9/2)	(5/2, 3, 7/2)	(5/2, 3, 7/2)	(7/2, 4, 9/2)	(5/2, 3, 7/2)
C2	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)
C3	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
C4	(3/2, 2, 5/2)	(2/3, 1, 3/2)	(2/3, 1, 3/2)	(2/3, 1, 3/2)	(2/3, 1, 3/2)
C5	(2/3, 1, 3/2)	(2/3, 1, 3/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(3/2, 2, 5/2)

DM1: The Chief; DM2: Purchasing Manager; DM3: Production Manager; DM4: QC Manager; DM5: Warehousing Manager

A.3 Fuzzy weights of criteria

Criteria	**Fuzzy weights**				
	DM1	**DM2**	**DM3**	**DM4**	**DM5**
C1	(0.037, 0.037, 0.037)	(0.029, 0.029, 0.029)	(0.027, 0.027, 0.027)	(0.026, 0.028, 0.028)	(0.027, 0.026, 0.027)
C2	(0.022, 0.025, 0.027)	(0.021, 0.025, 0.026)	(0.019, 0.023, 0.024)	(0.021, 0.024, 0.025)	(0.019, 0.023, 0.024)
C3	(0.007, 0.007, 0.007)	(0.008, 0.009, 0.009)	(0.007, 0.008, 0.009)	(0.006, 0.006, 0.007)	(0.007, 0.008, 0.009)
C4	(0.009, 0.010, 0.011)	(0.009, 0.011, 0.012)	(0.008, 0.009, 0.011)	(0.007, 0.007, 0.008)	(0.008, 0.009, 0.009)
C5	(0.009, 0.009, 0.010)	(0.011, 0.014, 0.017)	(0.019, 0.023, 0.024)	(0.019, 0.025, 0.025)	(0.019, 0.023, 0.024)
$\tilde{\varphi}^*$	(0.419, 0.419, 0.419)	(0.299, 0.299, 0.299)	(0.299, 0.299, 0.299)	(0.246, 0.246, 0.246)	(0.299, 0.229, 0.229)

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