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Supplier Performance Evaluation in Supply Chain Management Using Fuzzy TOPSIS Based on Vertex Method

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ABSTRACT

Supplier selection is a critical yet complex process in the competitive automotive industry, often hampered by subjective judgment and uncertainty. This study proposes a hybrid fuzzy multi-criteria decision-making (MCDM) framework integrating fuzzy AHP and fuzzy TOPSIS to enhance selection reliability. Within this framework, fuzzy AHP determines the weights of criteria: profitability, relationship closeness, technological capability, conformance quality, and conflict resolution. Fuzzy TOPSIS, utilizing the vertex method for precise distance measurement, is then applied to rank alternatives. A case study of three Malaysian automotive suppliers demonstrates the framework's effectiveness. Results and comparative analyses confirm that this integrated approach provides a robust, stable, and flexible decision-support tool for managing imprecise information in industrial procurement.

1. Introduction

In the contemporary globalized market, supplier selection has become a critical strategic decision for organizations. This is particularly evident in the automotive manufacturing sector, where companies depend heavily on external sourcing for components [1]. The ability to identify the right supplier directly influences production cost-effectiveness, product quality, and delivery performance [2]. Consequently, organizations require robust Multi-Criteria Decision Making (MCDM) tools to navigate these complex variables.

The evolution of supplier selection has transitioned from simple cost-based models to complex MCDM frameworks. According to [1] and [2], modern supply chains must balance conflicting objectives such as quality, lead time, and service level. However, traditional MCDM models often utilize "crisp" data, which fails to account for the ambiguity of human judgment.

To address this, Zadeh introduced Fuzzy Set Theory [5], which provides a mathematical framework for modeling linguistic uncertainty. In the context of decision-making, Bellman and Zadeh [10] argued that many goals and constraints in real-world situations are fuzzy rather than precise.

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Recent literature highlights the effectiveness of hybrid models; for instance, Mardani et al. [4] reviewed two decades of fuzzy MCDM applications, noting a significant shift toward integrated techniques like Fuzzy AHP (FAHP) and Fuzzy TOPSIS.

FAHP, built upon Saaty's Analytic Hierarchy Process [6], allows for the determination of criteria weights by accommodating the imprecision of expert opinions [3]. Meanwhile, Fuzzy TOPSIS ranks alternatives based on their distance from the "ideal" solution [7]. A critical development in this field is the Vertex Method, which simplifies the calculation of distances between fuzzy numbers, ensuring more consistent and computationally efficient rankings [7][11].

The integration of fuzzy logic into multi-criteria frameworks has proven essential for addressing the cognitive limitations of decision-makers when faced with complex industrial trade-offs [12]. Recent studies by Rostamzadeh et al. [13] emphasize that while AHP is effective for structuring hierarchies, its combination with TOPSIS enhances the reliability of the final ranking by considering both positive and negative ideal benchmarks. This is particularly relevant in the automotive sector, where supply chain disruptions necessitate a shift toward "resilient" supplier selection criteria [14]. Furthermore, the application of the vertex method within these models has been lauded for its computational transparency; as noted by Sun [15], the method effectively avoids the complexities of fuzzy arithmetic while preserving the essential geometric properties of triangular fuzzy numbers. This efficiency allows for a more "dynamic" selection process, enabling firms to update supplier rankings rapidly as market conditions evolve [16]

Despite the advancement in MCDM models, many industries still struggle to integrate qualitative factors such as supplier flexibility and technological capability—into their selection process [3]. In the Malaysian automotive industry, where competition is high and quality standards are stringent, there is a lack of practical frameworks that can reconcile these subjective expert opinions with quantitative metrics. Current methods often overlook the "fuzziness" of human reasoning, leading to suboptimal supplier partnerships. Hence, the main aim of this research is to evaluate supplier performance using an integrated Fuzzy MCDM approach.

The subsequent sections of this paper are organized to provide a comprehensive evaluation of the proposed supplier selection framework. Section 2 details the methodology, outlining the mathematical procedures of the integrated Fuzzy AHP and Fuzzy TOPSIS models, specifically emphasizing the application of the vertex method to manage linguistic uncertainty. Following the methodological exposition, Section 3 presents the results derived from the case study within the Malaysian automotive industry, illustrating the criteria weights and the final ranking of supplier alternatives. Finally, Section 4 offers a conclusion that synthesizes the research findings, discusses the practical implications for supply chain management, and suggests directions for future research in multi-criteria decision-making.

2. Methodology

2.1 Research Data

This section details the analytical framework developed to evaluate and select suppliers through a Multi-Criteria Decision Making (MCDM) approach within a fuzzy environment. The proposed methodology is adapted from the fuzzy TOPSIS framework established by Mardani et al. [4], which is specifically designed to reconcile the interplay between quantitative metrics and qualitative criteria under linguistic uncertainty. To ensure consistency in the evaluation process, the qualitative assessments provided by the experts were transformed using a standardized linguistic scale. As shown in Table 1, the linguistic variables for the importance weight of each criterion range from 'Very Low' to 'Very High,' each corresponding to specific triangular fuzzy numbers (TFNs). These TFNs allow for the mathematical representation of subjective expert opinions during the Fuzzy AHP phase. Furthermore, the performance ratings for each supplier alternative were evaluated based on the scale defined in Table 2, which maps qualitative performance levels to a fuzzy range of [0, 10].

Table 1
The importance weight of each criterion given by the decision makers

Criteria \ Decision Makers	$\boldsymbol{D_1}$	$\boldsymbol{D_2}$	$\boldsymbol{D_3}$
C_1	H	VH	MH
C_2	VH	VH	VH
C_3	VH	H	H
C_4	VH	VH	VH
C_5	M	MH	MH

Table 2
The result obtained from ratings given by decision makers

Criteria	**Alternative**	**Linguistic Variable**
C_1	A_1	MG
	A_2	G
	A_3	VG
C_2	A_1	G
	A_2	VG
	A_3	MG
C_3	A_1	F
	A_2	VG
	A_3	G
C_4	A_1	VG
	A_2	VG
	A_3	G
C_5	A_1	F
	A_2	VG
	A_3	G

2.2 Subjective weighting using Fuzzy AHP

To determine the relative importance of the evaluation criteria, this study employs the Fuzzy Analytic Hierarchy Process (FAHP). While the traditional AHP developed by Saaty [6] provides a structured approach for decomposing complex decisions, it often fails to account for the inherent uncertainty and "fuzziness" of human perception. By integrating fuzzy set theory [5], FAHP allows decision-makers to express their preferences using linguistic variables, which are then modeled as triangular fuzzy numbers to ensure a more realistic representation of subjective judgments [3]. The execution of the FAHP follows a systematic multi-step procedure as outlined below:

Step 1: Construct the hierarchy.
The decision-making process begins by constructing a hierarchical structure as shown in Figure 1 that represents the problem, starting with the main objective, followed by relevant criteria, and finally the decision alternatives. Once the hierarchy is established, decision makers conduct pairwise

comparisons at each level to determine the relative importance or weight of each element. This comparison process helps prioritize factors based on their contribution to the overall goal. To ensure effective prioritization, the problem must be clearly defined, objectives identified, key criteria determined, and the structure organized into levels consisting of criteria, sub-criteria, and alternatives.

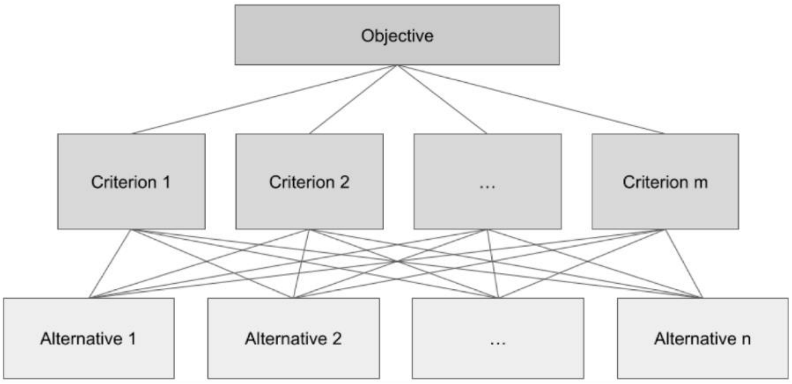

Fig. 1. Hierarchical model (Schiavon et al., 2023)

Step 2: Make pairwise comparisons.

Pairwise comparisons are made to assess the importance of elements relative to higher-level criteria, and the results are recorded in a judgment matrix using a defined scale as the one shown in Table 3. The number of required judgments is given by $n(n-1)$.

Table 3
Linguistic Variable for the Importance Weight of Each Criteria (Talukdar, & Dutta, 2019)

Linguistic Variables	**Triangular Fuzzy Numbers**
Very Low (VL)	(0.0, 0.0, 0.1)
Low (L)	(0.0, 0.1, 0.25)
Medium Low (ML)	(0.15, 0.3, 0.45)
Medium (M)	(0.35, 0.5, 0.65)
Medium High (MH)	(0.55, 0.7, 0.85)
High (H)	(0.8, 0.9, 1.0)
Very High (VG)	(0.9, 1.0, 1.0)

Step 3: Calculate weight

Each criterion or sub-criterion is compared with every other one using a relative importance scale (e.g., 1–9) to express decision-makers' preferences. This structured scale helps represent subjective judgments, and the results are used to calculate the relative weights of each criterion.

Step 4: Check consistency

$CR = CI/IR$

where,

CI - Measure the degree of inconsistency in the pairwise comparison matrix. It is calculated based on the eigenvalue of the matrix.

IR - Random index represents the average consistency index of randomly generated matrices of the same size. Values for IR are shown in Table 4 below. The CR helps determine the level of consistency. It is necessary for CR to be less than 0.1 to be considered as consistent.

Table 4
Random Index purposed by Saaty (1980).

Matrix size, *n*	**Index of Randomness, *IR***
1	0
2	0
3	0.52
4	0.89
5	1.11
6	1.25
7	1.35
8	1.40
9	1.45
10	1.49

2.2 Ranking alternatives using Fuzzy TOPSIS

Following the determination of criteria weights, the selection process proceeds to the ranking of alternatives. This study utilizes the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS), as extended by Chen [7]. This method is particularly effective for evaluating supplier performance because it identifies the alternative that is closest to the Fuzzy Positive Ideal Solution (FPIS) and furthest from the Fuzzy Negative Ideal Solution (FNIS) [3]. By employing linguistic variables to represent decision-makers' ratings, Fuzzy TOPSIS provides a robust mechanism for handling the inherent subjectivity found in supply chain evaluations [11]. The Fuzzy TOPSIS procedure is executed through the following formalized steps:

Step 1: Definition of criteria and alternatives

The decision problem is defined by a set of *n* criteria, C = { $C_1, C_2, C_3, \ldots, C_n$ }, and a set of *m* potential suppliers (alternatives), *A = {* $A_1, A_2, \ldots, A_m$ }

Step 2: Assignment of fuzzy weights and ratings.

A group of *K* decision-makers *D = {* $D_1, D_2, D_3, \ldots, D_k$ *},* assess the importance of the criteria and the performance of the alternatives using linguistic variables. These qualitative assessments (e.g., "Very High," "Medium," "Low") are mapped to corresponding triangular fuzzy numbers (TFNs).

Step 3: Aggregation of fuzzy weights and ratings.

The individual fuzzy weights provided by the *K* decision-makers for each criterion *j* are aggregated using the fuzzy arithmetic mean:

$$\tilde{w}_j = \frac{1}{K}\left(\tilde{w}_j^1 + \tilde{w}_j^2 + \tilde{w}_j^3\right)$$

where $\tilde{w}_j^k$ represents the importance weight assigned by the k^{th} decision-maker. Similarly, the fuzzy ratings for each alternative *i* under criterion *j* are aggregated to form the fuzzy decision matrix.

Step 4: Construction of the fuzzy decision matrix.

The aggregated fuzzy ratings and weights are organized into a fuzzy decision matrix $\tilde{D}$, where each element $\tilde{x}_{ij}$ represents the performance of alternative A_i with respect to criterion C_j.

$$\begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots\cdots & C_m \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots\cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots\cdots & \tilde{x}_{2n} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots\cdots & \tilde{x}_{mn} \end{bmatrix} \end{array}$$

Step 5: Calculation of the Weighted Normalized Fuzzy Decision Matrix.

The normalized fuzzy decision matrix $\tilde{R}$ is computed, and the weighted normalized fuzzy decision matrix $\tilde{V}$ is constructed by multiplying the normalized ratings by their corresponding fuzzy weights:

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j$$

where $\tilde{r}_{ij}$ denotes the elements of the normalized fuzzy decision matrix.

Step 6: Determination of FPIS and FNIS.

The Fuzzy Positive Ideal Solution A^* and the Fuzzy Negative Ideal Solution A^- are identified. These represent the best and worst possible outcomes, respectively, and are defined as:

$$A^* = \left(\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*\right)$$
$$A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\right)$$

where $\tilde{v}_j^* = \max\left\{v_{ij4}\right\}$ for benefit criteria and $\tilde{v}_j^- = \min\left\{v_{ij1}\right\}$ for cost criteria.

Step 7: Distance Calculation using the Vertex Method.

The distance of each alternative from A^* and A^- is calculated using the vertex method [3]. For two triangular fuzzy numbers $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$, the distance d_v is defined as:

$$d_v(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}\left[\left(m_1 - n_1\right)^2 + \left(m_2 - n_2\right)^2 + \left(m_3 - n_3\right)^2\right]}$$

The total distances for each supplier i are:

$$d_i^* = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^*) \text{ and } d_i^- = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^-).$$

Step 8: Determination of the Closeness Coefficient and Ranking.

The closeness coefficient CC_i for each alternative is calculated to determine its relative proximity to the ideal solution:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}$$

Suppliers are ranked in descending order of their CC_i values. The alternative with the highest CC_i is considered the optimal choice. This model is recognized for its computational efficiency and its robust ability to handle linguistic ambiguity in complex supply chain scenarios [7][10].

3. Results and Discussion

3.1 Case Study

This section details the empirical application of the integrated Fuzzy AHP-TOPSIS framework to a supplier selection problem under uncertainty. By utilizing Fuzzy AHP to establish criteria weights through expert linguistic judgments and Fuzzy TOPSIS to rank alternatives via the vertex method, the model effectively bridges the gap between qualitative assessments and quantitative ranking. This systematic approach ensures a consistent evaluation of supplier performance, demonstrating the model's robustness in handling the inherent imprecision of real-world decision-making environments.

The study addresses the strategic need for supplier collaboration in the Malaysian automotive sector to enhance supply chain competitiveness and mitigate procurement risks. A panel of three industrial experts (D_1, D_2, D_3) evaluated three candidate suppliers (A_1, A_2, A_3)across five key performance dimensions: profitability C_1, relationship closeness C_2, technological capability C_3, conformance quality C_4, and conflict resolution C_5as shown Figure 2. This case study validates the hybrid fuzzy MCDM framework as a practical tool for identifying optimal long-term partners in high-stakes manufacturing scenarios.

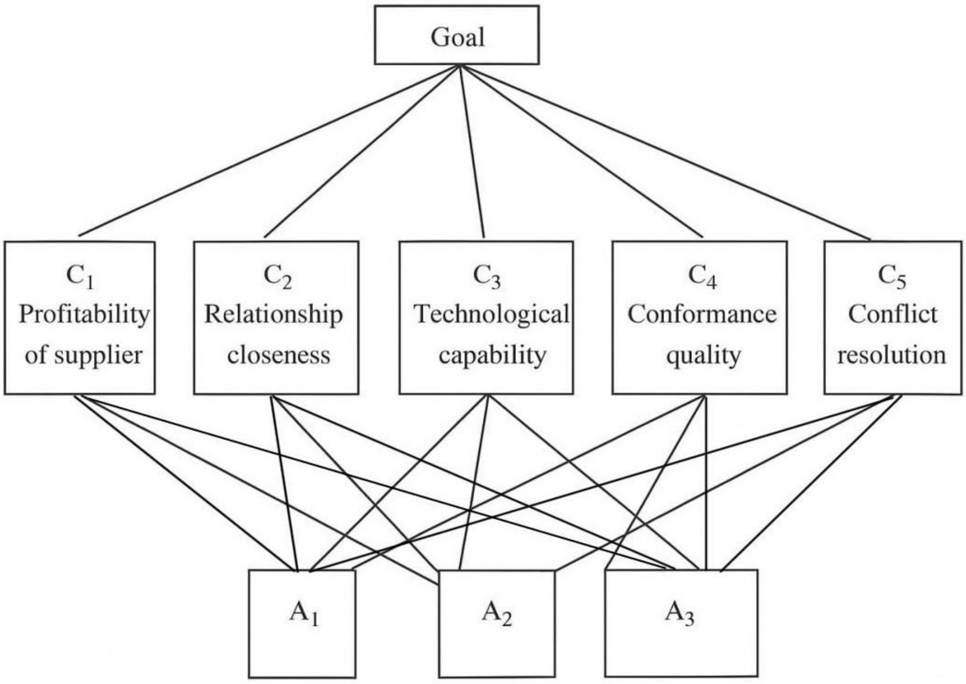

Fig. 2. Hierarchy structure for supplier selection.

3.2 Criteria Weight Determination via Fuzzy AHP

The relative importance of the five identified criteria was determined using the Fuzzy AHP method. The priority weights, which reflect the collective evaluation of the decision-making panel, are presented in Table 5. The results indicate that relationship closeness C_2 and conformance quality C_4 are the most significant factors, each holding a weight of 0.22, followed closely by technological capability C_3 at 0.21. These findings underscore the industry's emphasis on supplier reliability and technical proficiency over purely financial metrics.

Table 5
Calculated criteria weight based on AHP method

Criteria	Weight
C_1	0.19
C_2	0.22
C_3	0.21
C_4	0.22
C_5	0.16

3.2 Supplier Evaluation and Ranking via Vertex Method

The evaluation phase commenced with the aggregation of fuzzy weights for each criterion, as shown in Table 6. These aggregated weights were utilized to construct the weighted normalized fuzzy decision matrix. Subsequently, the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) were identified for each candidate to measure their relative performance. The calculated distances from these ideal points are summarized in Table 7. The final selection was based on the Closeness Coefficient CC_i, which determines the prioritization of the candidates. As detailed in Table 8, candidate A_1 achieved the highest CC_i value, indicating it is the most suitable supplier based on the established criteria.

Table 6
Aggregated Fuzzy Weight, w_j

Criteria	Aggregated Fuzzy Weight, w_j
C_1	(0.75, 0.87, 0.95)
C_2	(0.9, 1.0, 1.0)
C_3	(0.83, 0.93, 0.78)
C_4	(0.9, 1.0, 1.0)
C_5	(0.48, 0.63,0.78)

The calculated normalized fuzzy decision matrix, *D* is given by

$$\begin{bmatrix} (0.5,0.7,0.9) & (0.65,0.8,0.95) & (0.35,0.5,0.65) & (0.9,1,1) & (0.35,0.5,0.65) \\ (0.65,0.8,0.95) & (0.9,1,1) & (0.9,1,1) & (0.9,1,1) & (0.9,1,1) \\ (0.9,1,1) & (0.5,0.7,0.9) & (0.65,0.8,0.95) & (0.65,0.8,0.95) & (0.65,0.8,0.95) \end{bmatrix}$$

Calculated weighted normalized fuzzy decision matrix is given as

$$\begin{bmatrix} (0.095, 0.133, & (0.143, 0.176, & (0.074, 0.105, & (0.198, 0.220, & (0.056, 0.080, \\ 0.171) & 0.209) & 0.137) & 0.220) & 0.104) \\ (0.124, 0.152, & (0.198, 0.220, & (0.189, 0.210, & (0.198, 0.220, & (0.144,0.160, \\ 0.181) & 0.220) & 0.210) & 0.220) & 0.160) \\ (0.171, 0.190, & (0.110, 0.154, & (0.137, 0.168, & (0.143, 0.176, & (0.104, 0.128, \end{bmatrix}$$

Table 7
FPIS and FNIS for Each Candidate

Candidate	FPIS	FNIS
A_1	0.196	0.061
A_2	0.061	0.196
A_3	0.124	0.124

Table 8
Closeness Coefficients and Rankings

Candidate	FPIS	FNIS
A_1	0.196	0.061
A_2	0.061	0.196
A_3	0.124	0.124

3.2 Comparative Analysis and Model Validation

To validate the robustness of the proposed framework, a comparative analysis was performed between the Vertex method and the Hamming distance method. The results of this comparison are presented in Table 9.

Table 9
Comparison between two distance methods

Alternative	**Vertex Method,** CC_i	**Hamming Distance,** CC_i	**Ranking**
A_1	0.763	0.8241	1
A_2	0.500	0.7145	2
A_3	0.237	0.6285	3

The analysis reveals that while the absolute values of the closeness coefficients differ slightly between the two methods, the final ranking of the candidates remains identical $(A_1 > A_2 > A_3)$. This consistency across different distance measures demonstrates the reliability and stability of the Fuzzy TOPSIS method. The findings suggest that the integrated FAHP-TOPSIS approach is a dependable tool for managing the complexities and linguistic ambiguities inherent in industrial supplier selection.

4. Conclusions

This study presents an integrated fuzzy multi-criteria decision-making (MCDM) framework designed for supplier prioritization within the Malaysian automotive sector. The evaluation model incorporates five strategic and operational dimensions: profitability, relationship closeness, technological capability, conformance quality, and conflict resolution. To address the inherent uncertainty in expert judgment, the Fuzzy Analytic Hierarchy Process (FAHP) was utilized to derive relative criteria weights. Subsequently, Fuzzy TOPSIS augmented by the vertex method for calculating distances between trapezoidal fuzzy numbers was employed to determine the final supplier rankings. The findings provide a structured selection of the most suitable supplier based on the collective evaluations of the decision-making panel.

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