



## Optimizing Decision Accuracy in Supplier Selection: A Mathematical Framework Employing Triangular Fuzzy Logic

Joyeshree Biswas<sup>1\*</sup>, Iqtiaar Md Siddique<sup>2</sup>

<sup>1</sup>Department of Industrial and Systems Engineering, The University of Oklahoma, 660 Parrington Oval, Norman, OK 73019-0390, USA.

<sup>2</sup> Department of Industrial, Manufacturing & Systems Engineering, University of Texas at El Paso, US.

\*[joyeshree@ou.edu](mailto:joyeshree@ou.edu)

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### ABSTRACT

This study presents a comprehensive mathematical model employing triangular-based fuzzy decision-making techniques to enhance the precision of supplier selection processes. Supplier selection is a critical aspect of supply chain management, and decision-making in this domain involves dealing with uncertainties and imprecise information. The proposed model leverages triangular fuzzy logic to capture and manage uncertainties associated with supplier evaluation criteria. By integrating mathematical frameworks, the model provides a systematic approach to supplier selection, ensuring a more accurate and robust decision-making process. The methodology involves developing a set of triangular fuzzy numbers to represent the imprecise nature of decision criteria such as cost, quality, and delivery time. These fuzzy numbers are then processed through mathematical algorithms to derive a comprehensive evaluation score for each supplier. The model's effectiveness is validated through empirical case studies and comparisons with traditional supplier selection methods, highlighting its ability to handle uncertainty and enhance decision precision. This research contributes to the field of supply chain management by offering a sophisticated yet practical approach to supplier selection, aligning with the growing need for data-driven decision-making processes in contemporary business environments. The proposed model provides valuable insights for practitioners seeking to optimize supplier selection strategies and improve overall supply chain performance.

**Key words:** Supplier selection, Analytical Hierarchy Process, Fuzzy-AHP

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### INTRODUCTION

Today, the competition between corporations grows fast. In the realm of supply chain management, effective supplier selection stands as a pivotal decision-making process that profoundly influences organizational performance. The complexity inherent in this task, characterized by multifaceted criteria and uncertain information, necessitates robust methodologies to enhance decision accuracy. Traditional approaches often struggle to accommodate the inherent vagueness and imprecision prevalent in real-world decision environments. To address this challenge, the utilization of fuzzy logic has gained considerable traction, offering a means to model and manage uncertainty effectively. This paper proposes a novel mathematical framework leveraging triangular fuzzy logic to optimize decision accuracy in supplier selection processes. Triangular fuzzy logic, an extension of classical fuzzy logic, offers a structured approach to represent and handle uncertainty through triangular membership functions. By incorporating this framework into supplier selection methodologies, decision-makers can navigate the ambiguity inherent in evaluating supplier capabilities, performance metrics, and other relevant criteria.

The integration of triangular fuzzy logic not only facilitates the representation of imprecise information but also enables the development of robust decision models capable of capturing the subjective judgments of

stakeholders. Through a systematic exploration of supplier attributes and preferences, the proposed framework aims to enhance the accuracy and reliability of supplier selection decisions, thereby fostering improved supply chain performance and competitiveness. This paper delineates the theoretical foundations of triangular fuzzy logic and elucidates its application in the context of supplier selection. Furthermore, it outlines a structured methodology for employing triangular fuzzy logic to model and evaluate supplier attributes, facilitating informed decision-making processes. Through empirical validation and comparative analysis, the efficacy of the proposed framework is demonstrated, highlighting its potential to mitigate uncertainty and enhance decision accuracy in supplier selection scenarios.

This research endeavours to contribute to the advancement of supplier selection methodologies by presenting a robust mathematical framework grounded in triangular fuzzy logic. By offering a structured approach to handle uncertainty and imprecision, the proposed framework empowers decision-makers to make informed, data-driven choices, thereby optimizing supply chain performance and fostering organizational competitiveness in dynamic business environments. In today's rapidly growing corporate landscape, competition among companies is intense. Success in this highly competitive environment is often tied to how well companies design and manage their supply chains, as those who excel in these aspects tend to be more profitable and consequently stronger in the market [21]. Within the realm of business activities, decision-making stands out as one of the most crucial. Managers rely on reliable and accurate forecasts to inform their decisions, and this necessitates the consideration of scientific criteria. A typical decision-making problem involves selecting the most suitable alternative based on at least one goal or criterion from a cluster of alternatives [2]. This decision-making process extends to various aspects of business operations, including the critical task of choosing a raw material supplier in the supply chain. The selection of a supplier for partnership is a pivotal step in establishing a successful alliance, with far-reaching implications for the buyer-supplier relationship. When executed correctly, this process paves the way for higher quality and longer-lasting relationships [3]. For corporations, establishing strong relationships with suppliers is instrumental in gaining cost advantages through timely and high-quality deliveries. Consequently, supplier evaluation holds strategic importance for companies [1]. Various processes exist for supplier selection and evaluation, such as AHP, Fuzzy-AHP, ANP, TOPSIS, MCDM, Goal programming, and Supply chain networking. AHP, for instance, involves pair-wise comparison but may fall short in considering all criteria of supplier selection in practical scenarios. This paper proposes a model that compares the AHP and Fuzzy-AHP methods for supplier selection in the context of a cement industry. The study incorporates twenty-one criteria for supplier selection, encompassing both subjective and objective factors. Building on the foundation laid by Dickson in 1966, who presented 23 supplier selection criteria with assigned rankings, the paper delves into recent studies on supplier evaluation and selection across diverse industries. Examples include the Baby Food Manufacturing Industry (Weber, 1996) [4], Wooden Furniture Industry (Yahya and Kingsman, 1999) [5], Agricultural and Construction Equipment Industry (Liu et al., 2000), Telecommunications Industry (Narasimhan et al., 2001) [6], and Food Manufacturing Industry (Çebi and Bayraktar, 2004) [7]. While there are a few studies on performance evaluation in the retail industry (Wagner et al., 1989) [8], the focus remains on understanding supplier selection dynamics. The study concludes by comparing the two methods, AHP and Fuzzy-AHP, and determining their relative importance through a real case study in a cement industry. Data for the study were collected from the industry, and the supplier selection process was first executed using the AHP method, followed by the Fuzzy-AHP method. Noman et. al. and Biswas et al. (2024) describe in their different papers regarding data retrieval and can medically sector analysis where supplier selection data analysis system required their prompt responses for making decisions. They also consider decision making factor for their device decision weightage and machine learning algorithm from where this study will work for future extension [1,14-20].

In essence, this comprehensive exploration underscores the critical role of supplier selection in the success of corporations, emphasizing the need for robust methodologies like AHP and Fuzzy-AHP. The real-world application of these methods in a cement industry case study adds practical insights, contributing to the ongoing discourse on effective decision-making processes in the ever-evolving business landscape. In this paper the proposed model is to compare the AHP and Fuzzy-AHP method for supplier selection in the cement industry. We consider twenty-one criteria for supplier selection including both subjective and objective factors. Dickson (1966) outlined 23 criteria for supplier selection and assigned rankings to each of these criteria. Recent

investigations into supplier evaluation and selection span various industries, with studies conducted in the Baby Food Manufacturing Industry by Weber (1996) [4], the Wooden Furniture Industry by Yahya and Kingsman (1999) [5], the Agricultural and Construction Equipment Industry by Liu et al. (2000), and the Telecommunications Industry by Narasimhan et al. (2001) [6]. Additionally, research in the Food Manufacturing Industry has been conducted by Çebi and Bayraktar (2004) [7]. Notably, Wagner et al. (1989) [8] undertook performance evaluation studies specifically in the retail industry. These diverse investigations collectively contribute to a comprehensive understanding of supplier selection criteria and methodologies across various sectors, offering valuable insights into the evolving landscape of procurement and supplier management. Finally, we compare the two methods AHP vs. Fuzzy-AHP and the determination of their relative importance in real case study in a cement industry from where the necessary data was collected. At first step the supplier is selected through AHP method and then it is in Fuzzy-AHP method.

### LITERATURE REVIEW

The Analytic Hierarchy Process (AHP), introduced by Saaty in 1980, stands as a multi-criteria decision-making approach that enhances rational decision-making by systematically breaking down complex problems into smaller constituent parts. This decomposition allows decision-makers to concentrate on a limited number of elements concurrently, facilitating a more focused analysis. The AHP unfolds in two distinct phases: the construction of the hierarchy and the subsequent evaluation of its components, as outlined by Saaty (1980) and Vargas (1990) [9]. AHP emerges as a particularly well-suited method for addressing complex decisions that involve the comparison of decision elements challenging to quantify. The underlying assumption is that, when confronted with a complex decision, individuals naturally tend to group decision elements based on their shared characteristics. This technique proves valuable for decision-making scenarios characterized by a limited number of choices, each possessing a few distinct attributes, some of which may be challenging to formalize. Its applicability becomes even more pronounced in team-based decision-making settings. The methodology involves the construction of a hierarchy or ranking of decision elements, followed by comparisons between each possible pair within each cluster, represented as a matrix. This matrix-based approach facilitates the determination of weights for each element within a cluster or level of the hierarchy. Additionally, the consistency ratio is computed, providing a metric to assess the coherence of the data. In essence, AHP offers a structured and systematic framework for decision-making, especially in situations where the complexity of the decision requires breaking it down into manageable components. Its effectiveness is notable in scenarios where decision elements exhibit variability that may be challenging to precisely quantify. The method's reliance on hierarchical structuring and pairwise comparisons contribute to a comprehensive understanding of decision elements and their interrelationships, offering valuable insights for informed decision-making. Consequently, AHP finds its place as a valuable tool in academic research, particularly in the analysis of intricate decision-making processes within diverse contexts. At the heart of the Analytic Hierarchy Process (AHP) lies the pivotal task of determining the relative weights for ranking decision alternatives. Given the presence of  $n$  criteria in a designated hierarchy, the process entails constructing an  $n \times n$  pairwise comparison matrix denoted as  $A$ . This matrix encapsulates the decision maker's assessments regarding the relative significance of each criterion. Specifically, in row  $i$  (where  $i = 1, 2, 3, \dots, n$ ), pairwise evaluations are conducted with each criterion represented by the  $n$  columns. Defining the element  $(i,j)$  of  $A$  as  $a_{ij}$ , AHP employs a discrete scale ranging from 1 to 9. Here,  $a_{ij} = 1$  signifies equal importance between  $i$  and  $j$ ,  $a_{ij} = 5$  denotes a stronger importance of  $i$  over  $j$ , and  $a_{ij} = 9$  indicates an extremely higher importance of  $i$  over  $j$ . Intermediate values between 1 and 9 are interpreted accordingly. For consistency,  $a_{ij} = k$  automatically implies that  $a_{ji} = 1/k$ . Additionally, all diagonal elements  $a_{ii}$  of  $A$  must equal 1 as they denote the ranking of a criterion against itself. The relative weights of criterion can be determined from  $A$  by dividing the elements of each column by the sum of the elements of the same column. The relative weights of the criteria are derived from matrix  $A$  by dividing the elements of each column by the sum of the elements within that column. This computation results in a normalized matrix, denoted as  $N$ . The normalized weights in matrix  $N$  serve as numerical indicators presented to the decision maker, who assigns relative importance based on a predefined scale. Subsequently, a judgment matrix is prepared, representing an  $(n \times n)$  matrix, and normalized weights are calculated through the described process figure 1.

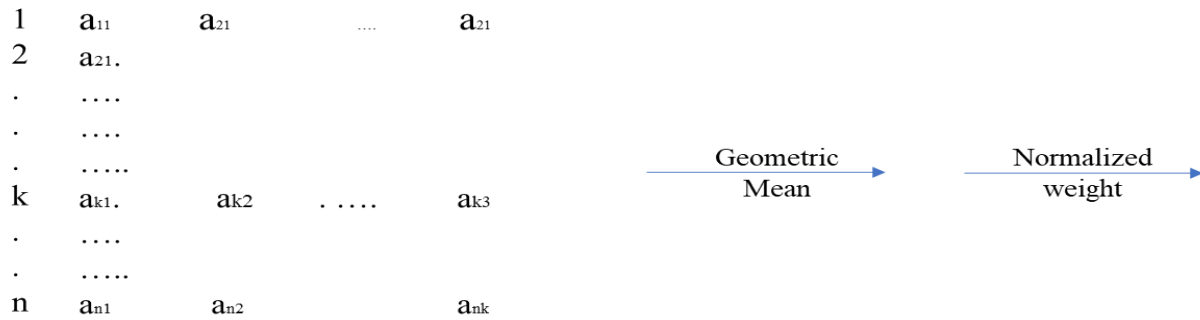


Fig 1: Geometric mean and normalized weights

In the comparison between alternatives or attributes  $i$  and  $j$ , where  $a_{ij}$  is the representing value, it is essential to ensure the consistency of the judgment matrix by adhering to the condition  $a_{ij} \cdot a_{jk} = a_{ik}$  for all values of  $i, j$ , and  $k$ . The sum of elements in a column, denoted as  $y_k = \sum a_{ij}$ , with  $i$  ranging from 1 to  $n$  and  $j$  from 1 to  $n$ , contributes to the assessment of consistency. Additionally, the geometric mean is computed as  $b_k = [(a_{k1}) \cdot (a_{k2}) \cdot \dots \cdot (a_{kn})]^{1/n}$ , where  $k$  varies from 1 to  $n$ . Saaty's traditional Analytic Hierarchy Process (AHP) utilizes a nine-point scale for pairwise comparisons in selecting the optimal alternative at each level of the goal. However, the application of Saaty's AHP method has been recognized with certain limitations [11]

Primarily, it finds extensive application in decision-making contexts where the criteria are clear-cut and well-defined. Secondly, AHP operates within an uneven judgment scale, introducing a notable imbalance in its handling of assessments. Thirdly, the approach overlooks the inherent uncertainty associated with translating subjective judgments into numerical values. Moreover, AHP tends to yield imprecise rankings, and lastly, the results are significantly swayed by the subjective judgments, choices, and inclinations of decision-makers.

Moreover, the requirements set by decision-makers in evaluating alternatives frequently involve ambiguity and multiple interpretations. Additionally, the inherent subjectivity and imprecision associated with human assessments of qualitative attributes pose challenges for conventional AHP, rendering it insufficient to explicitly capture decision-makers' requirements [11]. Recognizing the limitations of traditional AHP, particularly in handling uncertainty and imprecision in human preferences, an alternative approach emerges – the Fuzzy Analytic Hierarchy Process (Fuzzy AHP). This variant of AHP is introduced to address the compensatory nature of the original method and its incapacity to handle linguistic variables. Fuzzy AHP incorporates fuzzy sets into the pairwise comparison process, extending the conventional AHP framework to better accommodate uncertainties in decision-making. The Fuzzy AHP approach enables a more accurate representation of the decision-making process, acknowledging and embracing the inherent uncertainty and imprecision in human judgments. By introducing fuzzy logic, this variant of AHP provides a mechanism to capture and model the vagueness and subjectivity that conventional AHP struggles to handle effectively. In summary, the conventional AHP method, while widely used, exhibits shortcomings in handling uncertainty and imprecision inherent in human preferences. The advent of Fuzzy AHP addresses these limitations by incorporating fuzzy sets, offering a more nuanced and flexible framework for decision-makers to navigate complex and ambiguous decision environments.

**FUZZY ANALYTIC HIERARCHY PROCESS:**

The fuzzy Analytic Hierarchy Process (FAHP) technique represents an evolved analytical approach derived from the conventional AHP. Typically, expressing the uncertain preferences of decision-makers using precise values is challenging. Hence, FAHP is introduced to alleviate the uncertainty inherent in the AHP method by incorporating fuzzy comparison ratios. Chang's extent analysis in fuzzy AHP relies on the possibility degrees associated with each criterion. Based on the responses in the questionnaire, triangular fuzzy values for linguistic variables are assigned, and a pairwise comparison matrix is established for a specific level in the hierarchy. Subtotals for each matrix row are computed, resulting in a new  $(l, m, u)$  set. To derive the overall triangular fuzzy values for each criterion,  $l_i/\sum l_i, m_i/\sum m_i, u_i/\sum u_i$  (where  $i = 1, 2, \dots, n$ ) values are determined and utilized as the latest  $M_i(l, m_i, u_i)$  set for criterion  $M_i$  throughout the subsequent stages. In the subsequent phase, membership functions are formulated for each criterion, and intersections are identified by comparing each pair.

Within the fuzzy logic framework, each pairwise comparison entails identifying the intersection point, where the membership values at that point indicate the weight or degree of possibility. This membership value represents the likelihood or possibility associated with the given value. More specifically, for a particular criterion, the minimum degree of possibility in situations where its value exceeds others is regarded as the weight of that criterion before normalization. This methodology ensures that the assigned weight to each criterion accurately reflects its relative importance in the decision-making context. After determining weights for each criterion, a normalization step is implemented to derive the final importance degrees or weights for the hierarchical level. This normalization process guarantees comparability among weights, providing a clear indication of the significance of each criterion in the decision-making process.

To implement this hierarchical approach, the method outlined in [12] involves an extent analysis for each criterion. Each criterion, denoted as  $g_i$ , undergoes extent analysis, wherein the relative importance or degree of influence is assessed. This step-by-step evaluation for each criterion contributes to a comprehensive understanding of their respective contributions within the overall hierarchy. In essence, the fuzzy logic approach integrates intersection points and membership values to derive criterion weights, which are then normalized to obtain final importance degrees. The application of extent analysis, as per the methodology described in [12], ensures a systematic and thorough evaluation of each criterion's significance within the decision-making hierarchy. This methodological approach enhances the precision and effectiveness of decision-making processes by capturing and incorporating the nuances associated with fuzzy logic and extent analysis [13].

#### **PROBLEM STATEMENT:**

A well-established electronics industry in the United States encountered significant challenges in its supplier selection process. The traditional approach involved issuing tenders, scrutinizing supplier profiles, and subsequently engaging two or three suppliers in trial phases to evaluate the suitability of their raw materials for structure production. Unfortunately, this method led to delays in achieving profitability and success for the company. In response to these issues, we introduced a comprehensive supplier selection model to streamline the process. Instead of the time-consuming trial-and-error method, our proposed model emphasizes efficiency and precision in supplier evaluation. The new approach incorporates a thorough examination of supplier profiles, utilizing predefined criteria and attributes to systematically assess their capabilities. By implementing this model, the electronics industry aims to expedite the supplier selection process, minimizing delays in production and ensuring the timely acquisition of optimal raw materials. This innovative supplier selection model not only addresses the delays in profitability but also enhances the overall effectiveness of the electronics industry's supply chain. Through a more strategic and data-driven approach, the company anticipates improved decision-making in selecting suppliers that align with their specific needs and contribute to the timely and successful production of electronic structures.

#### **METHODOLOGY**

The application of the AHP to the complex problem usually involves below steps:

In the process of hierarchical decision-making, the complex problem is systematically deconstructed into smaller constituent elements, which are then organized in a hierarchical structure. Subsequently, a series of pairwise comparisons is conducted among these elements, employing a ratio scale to quantify their relative significance. The Eigenvalue method is then employed to estimate the weights of these elements, providing a numerical representation of their importance in the decision-making context. These relative weights are aggregated and synthesized, culminating in a comprehensive and final measurement for evaluating the decision alternatives. This methodical approach not only facilitates a systematic analysis of the problem but also ensures a rigorous and quantifiable basis for decision-making, contributing to a more informed and objective selection process. The Hierarchical structure is given below for our proposed model:

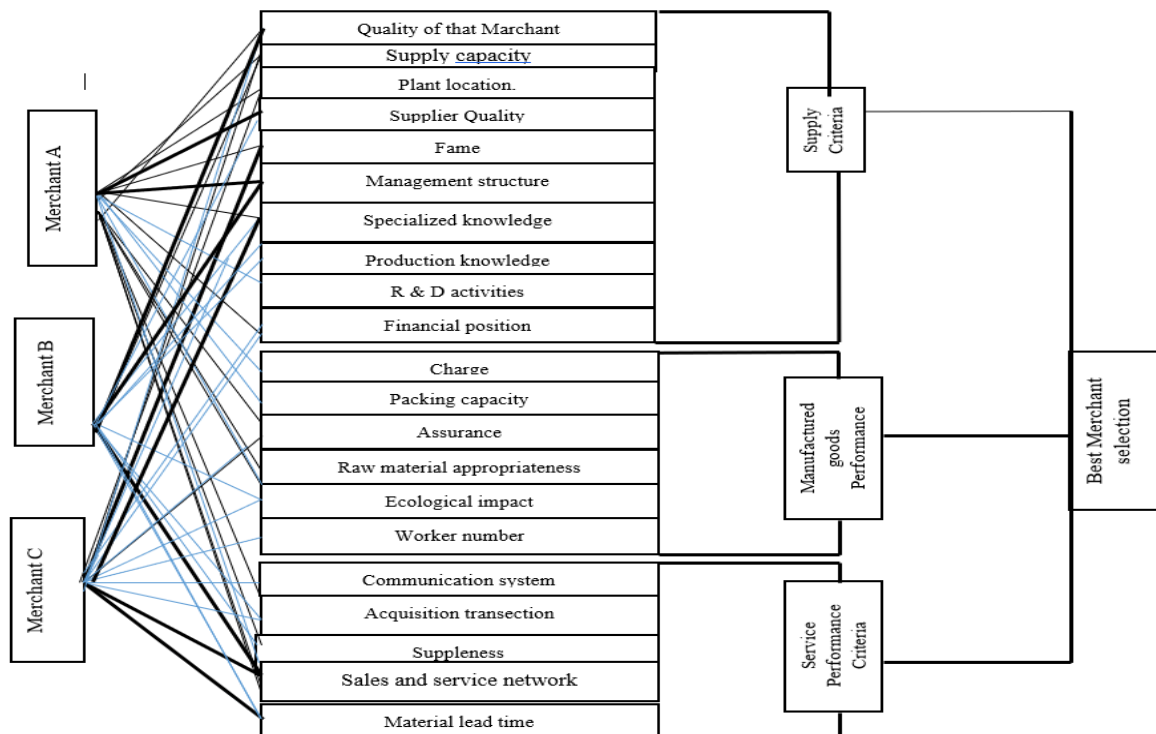


Fig 2: The Hierarchy of the supplier selection process

Saaty (1980) suggested conducting paired comparisons among various elements, emphasizing that the human brain is well-suited for evaluating the relative importance of two elements. As a result, he introduced the scale outlined in Table 1:

Table 1: Ratio scale of comparative judgement

Description	Status
Important Equally	2
Reasonably more important	4
Effectively more important	6
Very effectively more important	8
Exceptionally above important	10
Intermediary more important	1,3,5,7

Using the scale in Table 2 the squared matrix  $A_{n \times n}$  (Equation) is built:

$$A = [a_{ij}] 1 \leq i, j \leq n$$

Where,  $a_{ij}$  represents the comparison between element  $i$  and element  $j$ .

Table 2: The weight of selection criteria

S No.	Criteria	Mass
1	Value (A)	0.21
2	Supplier Quality (B)	0.39
3	Company Size (C)	0.41
4	Manufacturing plant (D)	0.21
5	Production capability (E)	0.89

The necessary table for AHP calculation is given below: this table calculation is done according to the process of pair-wise comparison method discussed above AHP methodology.

**Table 3:** pairwise comparison for criteria attributes

	Q	O	W	P	C
A	2	4	6	8	10
B	0.31	3	4	3	10
A= C	0.2	0.5	1	3	6
D	0.143	0.25	0.333	1	4
E	0.111	0.143	0.167	0.75	1
SUM	1.787	4.893	8.5	16.75	31

Normalized form from the above calculation is given below according to the pair-wise comparison:

**Table 4:** Normalized form for the criteria attributes

	QS	GS	SF	PR	MC	SUM
A <sub>NORM</sub> = QS	0.56	0.613	0.588	0.459	0.333	2.553
GS	0.186	0.204	0.235	0.262	0.259	1.146
SF	0.112	0.102	0.118	0.197	0.222	0.751
PR	0.08	0.57	0.039	0.066	0.148	0.384
MC	0.062	0.29	0.0196	0.016	0.037	0.1636

The over-all weight that is calculated from the above table is given below:

- $W_{QS} = 0.5106$
- $W_{GS} = 0.229$
- $W_{SF} = 0.1502$
- $W_{PR} = 0.0768$
- $W_{MC} = 0.033$

According to the method discussed above AHP methodology, we get the weight values of each supplier are given below:

**Table 5:** The weight values of each supplier candidate for sub-indicators

QS	GS	SF	PR	MC
Merchant A = 0.539	Merchant A = 0.547	Merchant A = 0.259	Merchant A = 0.143	Merchant A = 0.27
Merchant B = 0.297	Merchant B = 0.151	Merchant B = 0.105	Merchant B = 0.286	Merchant B = 0.613
Merchant C = 0.164	Merchant C = 0.302	Merchant C = 0.634	Merchant C = 0.571	Merchant C = 0.118

From above calculation the over-all score is calculated as follows:

**Table 6:** Score calculation and determination of overall score

Supplier name	Overall score
Merchant A	0.559
Merchant B	0.344
Merchant C	0.396

It is seen that the over-all score for Merchant A is 0.559 is largest value. Hence our selected supplier in AHP method is Merchant A and then the Merchant B, Merchant C.

**FUZZY-AHP CALCULATION**

**Table 7:** The linguistic variables and their corresponding fuzzy numbers:

Equally preferred (EP)	(1, 1, 1)
Weakly preferred (WP)	(2/3, 1, 3/2)
Fairly strongly preferred (FSP)	(3/2, 2, 5/2)
Very strongly preferred (VSP)	(5/2, 3, 7/2)
Absolutely preferred (AP)	(7/2, 4, 9/2)

**Table 8:** Priority vectors for the decision hierarchy

Variables in level 1	in Level 1 Priorities	Level 1 Variables in level 2	Level 2 Priorities	Level 2 Variables in level 3(Marchant)	Level 3 Priorities	
Merchant criteria	0.36	Quality system (QS)	0.1	A	0.13	
				B	0.57	
				C	0.29	
		Supply capacity (SC)	0.09		A	0.99
					B	0
					C	0
		Facility location (FL)	0.1		A	0.29
					B	0.35
					C	0.35
		Quality system of the supplier (QSS)	0.1		A	0.67
					B	0.33
					C	0
		Reputation (R)	0.8		A	0.57
					B	0.29
					C	0.132
Management and organization (MO)	0.1		A	0.99		
			B	0		
			C	0		
Technical knowledge (TK)	0.08		A	0.4		
			B	0.18		
			C	0.4		
Production technology (PT)	0.12		A	0.52		
			B	0.09		
			C	0.38		
R & D activities (RD)	0.1		A	0.67		
			B	0.33		
			C	0		
Financial position (FP)	0.1		A	0.57		
			B	0.29		
			C	0.132		
Product performance	0.36	Price (P)	0.15	A	0.26	
				B	0.36	
				C	0.37	
		Packaging and carrying capacity (PCC)	0.167		A	0.99
					B	0
					C	0
		Warranty (W)	0.22		A	0.132
					B	0.57
					C	0.29
		Material appropriateness (MA)	0.2		A	0.67
					B	0.33
					C	0



Service Performance	0.26	Environmental impact (EI)	0.2	A	0.29
				B	0.35
				C	0.35
		Employee number (EN)	0.06	A	0.4
				B	0.18
				C	0.4
		Communication system (CS)	0.22	A	0.26
				B	0.36
				C	0.37
		Purchase Transaction (PT)	0.18	A	0.57
				B	0.29
				C	0.132
		Flexibility (F)	0.15	A	0.99
				B	0
				C	0
Sales and service network (SS)	0.20	A	0.52		
		B	0.09		
		C	0.38		
Material lead time (ML)	0.23	A	0.26		
		B	0.36		
		C	0.37		

The overall score of each supplier is given below: In Table 10, each column of the matrix was multiplied by the priority weight at the top of the column and then those values were added up for each row. At the end, the priority weights of the alternatives with respect to supplier attribute were calculated. The same calculations have been applied to the sub-attributes of product performance attribute and service performance attribute and the priority weights of the alternatives with respect to product performance and service performance attributes have been calculated. The priority weights can be seen.

**Table 9:** Sub-attributes of supplier criteria

	QS	SC	FL	QSS	R	MO	TK	PT	RD	FP	APW
WEIGHT	0.1	0.09	0.1	0.09	0.12	0.1	0.12	0.12	0.1	0.1	
Marchant A	0.132	0.99	0.29	0.67	0.57	0.99	0.4	0.52	0.67	0.57	0.5814
Marchant B	0.57	0	0.35	0.33	0.29	0	0.18	0.09	0.33	0.29	0.2509
Marchant C	0.29	0	0.35	0	0.132	0	0.4	0.38	0	0.132	0.1746

**Table 10:** Sub-attributes of Product performance criteria:

	P	PCC	W	MA	EI	EN	APW
WEIGHT	0.17	0.167	0.22	0.2	0.2	0.06	
Marchant A	0.26	0.99	0.132	0.67	0.29	0.4	0.45457
Marchant B	0.36	0	0.57	0.33	0.35	0.18	0.3334
Marchant C	0.37	0	0.29	0	0.35	0.4	0.2207

**Table 11:** Sub-attributes of Service performance criteria:

	CS	PT	F	SSN	ML	APW
WEIGHT	0.22	0.18	0.18	0.2	0.23	
Merchant A	0.26	0.57	0.99	0.52	0.26	0.5018
Merchant B	0.36	0.29	0	0.09	0.36	0.2322
Merchant C	0.37	0.132	0	0.38	0.37	0.26626

**Table 12:** Main attributes of the Goal.

	Merchant Criteria	Product Performance	Service Performance	APW
WEIGHT	0.37	0.37	0.26	
Merchant A	0.68	0.55	0.60	0.61
Merchant B	0.35	0.43	0.33	0.37
Merchant C	0.28	0.32	0.37	0.32

The priority weights are shown in the table 13. The priority weights of each alternative with respect to the main attributes were combined and the priority weights of each alternative were determined. To shorten the process of supplier selection, Code block programming software and Excel sheet is used extensively to facilitate the comparison of main attributes, sub-attribute's, alternatives. The priority weights of each alternative in this solution process are (0.61, 0.37 and 0.32). It is clear from the final scoring that the supplier A is most preferred, and the supplier B is the next recognized supplier.

### CONCLUSIONS

Utilizing a standardized set of criteria or attributes, the process of supplier selection involves a comprehensive comparison to identify the most suitable supplier that aligns with the firm's needs, offering optimal value at a reasonable cost consistently. Optimal supplier selection not only diminishes procurement expenses but also enhances corporate competitiveness within the modern and multifaceted business landscape. Consequently, supplier selection stands out as a pivotal challenge in the multi-criteria decision-making process. This study employs both Analytic Hierarchy Process (AHP) and the Fuzzy-AHP approach to evaluate and identify the ideal supplier within the cement industry. While the AHP method relies on quantitative analysis to determine the right supplier, it falls short in considering crucial qualitative factors. To address this gap, the Fuzzy-AHP approach is introduced, encompassing three primary attributes and twenty-one sub-attributes for a more comprehensive supplier selection process. The Fuzzy-AHP method calculates the overall score of each supplier, aiding in the selection of the best supplier. AHP calculations in this study are executed using Math-lab software, while code-block programming is applied for the Fuzzy-AHP method to minimize errors and enhance accuracy, with minimal reliance on MS-Excel. To streamline the supplier selection process, information on suppliers, such as delivery dates, organizational certifications, and the supplier's quality system, can be efficiently retrieved from the ERP database. This integration significantly reduces the time-consuming efforts involved in supplier selection.

### FUTURE WORK:

Future work in this domain could focus on further refining the proposed mathematical framework by incorporating additional advanced techniques such as machine learning algorithms or hybrid fuzzy logic systems. Additionally, extending the application of the framework to diverse industries and exploring its scalability in large-scale supplier selection scenarios would be valuable. Furthermore, conducting longitudinal studies to assess the framework's performance over time and adapting it to evolving supply chain dynamics could enhance its practical relevance. Collaborative efforts with industry partners to implement and validate the framework in real-world settings would provide valuable insights and contribute to its refinement and generalization.

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