Supplier Selection under Epistemic Uncertainty Using a Bayesian BWM-Credal Ranking Integrated Fuzzy VIKOR Framework

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***Abstract*—In the context of managing the Supply Chain Management (SCM), a procurement company's primary goal is to purchase the appropriate goods and services at the appropriate cost, quality, and time to support the overall efficacy and efficiency of the supply chain. This involves selecting the right supplier, which contributes to cost reduction, fosters building relationships, and enhances operational efficiency. Ensuring that chosen suppliers support the company's economic growth while adhering to sustainability goals, less impact to environmental factors, and resilience criteria is crucial. This study proposes a hybrid multi-criteria decision-making technique that considers both quantitative and qualitative evaluation criteria to optimize and make an efficient supplier selection. The methodology incorporates the Best-Worst Method (BWM), which calculates the criterion weights and ranks them using a probabilistic scale using the credal ranking approach. Subsequently, the Fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) approach is then applied to rate potential suppliers based on the weights that were acquired. The supplier ranking of the VIKOR approach is compared against the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach, to ensure the stability of the VIKOR-based supplier ranking. The suggested model's usefulness is illustrated by a case study in the engineering and procurement sector, which validates its effectiveness and real-world applicability. This work offers valuable insights for decision-makers seeking reliable and efficient methods for supplier evaluation and selection.**

***Keywords*—supplier selection, Multi Criteria Decision Making (MCDM), best-worst method, fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), credal ranking**

I. Introduction

The Engineering, Procurement, and Construction (EPC) approach is a widely adopted project delivery method for large-scale industrial and infrastructure developments. Under this framework, a single contractor oversees design, material procurement, and construction, promoting efficient execution and clear accountability. One of the critical and crucial step involved in the successful execution of an EPC Project is the selection of suppliers for the procurement of materials, which ensures reliable material procurement and smooth execution across all project phases. The process involves evaluating multiple criteria such as cost, quality, delivery time, technical capability, and compliance with safety and environmental standards [1]. A systematic and structured approach helps mitigate risks and enhances project performance. Effective supplier selection strengthens the supply chain, enhances innovation, and contributes to long-term project success and competitiveness in the market.

With the growing complexity of global supply chains, organizations must evaluate suppliers using a wide range of criteria that often involve conflicting goals. Selecting the right supplier is vital for improving efficiency, reducing costs, and ensuring product quality and customer satisfaction. However, the process is complex, involving both measurable factors like cost and delivery time, and qualitative aspects such as innovation and sustainability.

Multi-Criteria Decision-Making (MCDM) techniques provide a systematic strategy for evaluating several possibilities based on a variety of often competing considerations in order to handle this complexity. They are particularly useful when decision-making involves both quantitative data and qualitative judgments, enabling decision-makers to balance trade-offs and consider stakeholder preferences. Among the various MCDM methods, the Best-Worst Method (BWM) [2] is gaining attention for its simplicity and consistency in deriving criteria weights from expert evaluations. BWM allows decision-makers to compare the most and least important criteria with the others, leading to more reliable weight calculations. Once the criteria weights are established, VlseKriterijumska Optimizacija I Kompromisno Resenje

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(VIKOR) can be used as a ranking tool that focuses on selecting a solution closest to the ideal, while also considering group consensus and compromise solutions—making it well-suited for situations where trade-offs are necessary.

Furthermore, since expert evaluations often involve uncertainty and imprecision, this study incorporates fuzzy logic to represent subjective judgments using linguistic variables modeled as fuzzy numbers. The integration of fuzzy sets into the MCDM framework [3] enhances the realism and flexibility of the decision-making process.

This study presents a comprehensive approach to supplier selection by integrating BWM, fuzzy logic, and VIKOR by applying uncertainty as well, since the decision makers may not be confident enough in the decision scale value being provided. The goal is to support organizations in making more consistent, transparent, and balanced decisions aligned with strategic objectives.

II. Literature Review

Pandian *et al.* [4] present a hybrid approach for supplier selection under uncertainty by combining factor analysis, Factor Relationship (FARE), and Grey Relational Analysis (GRA) methods. Based on survey data from 160 manufacturers, key evaluation factors are identified to build a structured assessment framework. The study focuses on balancing cost and carbon emissions, aiming for both economic efficiency and environmental responsibility.

Štreimikiene *et al.* [5] conducted an evaluation of supplier sustainability performance within Iran's automotive sector using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) technique, a method rooted in multi-criteria decision-making. The analysis focused on five key suppliers against a dozen of sustainability indicators such as environmental initiatives, product quality and customer satisfaction. It underscores the necessity of considering environmental, social, and operational dimensions in supplier assessments and calls for flexible, integrated strategies to achieve sustainability in rapidly evolving industrial contexts.

To increase the resilience and sustainability of supply chains, Varchandi *et al.* [6] and Sadjadi *et al.* [7] suggest an integrated supplier evaluation method that combines the Best-Worst Method (BWM) and Fuzzy TOPSIS. To find and rank pertinent evaluation criteria, the method depends on the professional opinions of supply chain experts. While Fuzzy TOPSIS ranks the providers according to their performance. BWM is used to establish the relative importance of these criteria by means of assigning a weightage. This method provides a systematic and flexible framework for supplier assessment.

Sadjadi *et al.* [7] present a robust extension of the Best-Worst Method (BWM) to improve reliability in multi-criteria decision-making. Their approach accounts for uncertainty and inconsistency in expert judgments, ensuring more stable and credible weight estimations. By incorporating robustness into the BWM framework, the study enhances its applicability in real-world decision problems where data and preferences are often imprecise. The findings demonstrate that the robust BWM provides decision-makers with more dependable outcomes compared to the traditional method.

Haryono *et al.* [8] performed a review of the literature to ascertain the principal factors and methodologies employed in food industry for selection of suppliers. The research involves the use of MCDM methodologies such Analytic Hierarchy Process (AHP), Step-wise Weight Assessment Ratio Analysis (SWARA), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), in conjunction with optimization strategies like linear programming. It underscores the efficacy of hybrid models—particularly the integration of AHP with linear programming—in enhancing supplier evaluation decisions specific to the food industry.

Tavana *et al.* [9] propose a hybrid approach for sustainably selecting suppliers by combining the Group Fuzzy Inference System (GFIS) with the Best-Worst Method (BWM). GFIS captures expert opinions expressed in linguistic terms, helping manage uncertainty, while BWM determines optimal criteria weights with reduced complexity. This integrated method supports more accurate and consistent decision-making across economic, environmental, and social dimensions.

Rasmussen *et al.* [10] examine the application of MCDM methods in the aerospace and defense sectors, where supplier selection involves strict standards for quality, compliance, and risk. They highlight traditional techniques like AHP and TOPSIS, along with advanced fuzzy logic-based models. These methods support structured, informed decision-making critical to safety and performance in such regulated industries.

Mohammadi and Rezaei [11] introduce a Bayesian-enhanced version of the BWM to better manage uncertainty in group decision-making. Unlike classical BWM, this approach models expert pairwise comparisons as probabilistic distributions, enabling more stable and accurate weight estimations. The Bayesian BWM improves flexibility and consensus-building, especially in complex multi-criteria scenarios. Through simulations and case studies, it proves more reliable for strategic applications like supply chain management and policy evaluation.

Cheraghalipour *et al.* [12] and Saner *et al.* [13] proposed an integrated decision support model that combines the BWM with Fuzzy VIKOR for successful choice of contractors in building projects. BWM is used to determine the significance of each criteria, whereas Fuzzy-VIKOR ranks contractors by identifying a compromise solution

Wang *et al.* [14] propose a hybrid MCDM approach for supplier selection in the textile industry using the Supply Chain Operations Reference (SCOR) model framework. The methodology integrates Fuzzy AHP to determine the weights of evaluation criteria and the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE II) to rank suppliers based on their performance. This combination effectively captures both qualitative and quantitative aspects of supplier assessment. The model proves practical for sourcing decisions in Vietnam's textile sector. However, it lacks validation across other industries and does not consider real-time data or comparisons with other MCDM techniques.

Vardin *et al.* [15] introduce a decision support model that combines the Best-Worst Method (BWM) for accurately weighting contractor selection criteria and Fuzzy-VIKOR for ranking contractors under uncertainty. The methodology applies pairwise comparisons via BWM to determine criteria importance and processes contractor performance data through Fuzzy-VIKOR to derive a compromise ranking.

Javad *et al.* [16] focuses on selecting suppliers for a Steel Company based on their green innovation ability. The Best-Worst Method (BWM) is applied to rank green supplier selection criteria, and Fuzzy TOPSIS is used to evaluate and rank alternative suppliers. Analyzing the supplier selection's key factors indicates that the green innovations criteria should be given more attention by the steel company in the green supplier selection. The findings of their study are useful in order to rate the suppliers according to their capacity for green innovation.

TABLE I. SUMMARY OF APPROACHES USED FOR SUPPLIER SELECTION

Author (s)	Methodology Used	Application Area	Key Contributions	Identified Gaps
Pandian *et al.* [4]	Factor Analysis, FARE, GRA	General Manufacturing	Developed a structured supplier selection framework under uncertainty; balanced cost and carbon emissions.	Needs validation in dynamic industry settings and with real-time data.
Štreimikiene *et al.* [5]	TOPSIS	Automotive (Iran)	Assessed sustainability performance of five suppliers using 12 indicators; emphasized environmental, social, and operational factors.	Context-specific; calls for broader application and integration in other industries.
Varchandi *et al.* [6] and Sadjadi *et al.* [7]	BWM + Fuzzy TOPSIS	Supply Chain Management	Created a flexible supplier evaluation model balancing resilience and sustainability under uncertainty.	Balancing conflicting priorities remains complex; limited to expert-driven data.
Haryono *et al.* [8]	AHP, SWARA, TOPSIS + Linear Programming	Food Industry	Reviewed MCDM methods; highlighted hybrid AHP + LP models for better food supplier selection.	Lacks empirical testing and extension to broader food sectors or global markets.
Tavana *et al.* [9]	Group Fuzzy Inference System (GFIS) + BWM	Sustainable Supply Chains	Managed uncertainty in linguistic judgments; supported triple bottom-line decision-making.	No performance benchmarking with other fuzzy-based MCDM methods.
Rasmussen *et al.* [10]	AHP, TOPSIS, Fuzzy MCDM Methods	Aerospace and Defense	Addressed supplier selection under high-risk, compliance-heavy contexts; emphasized structured evaluation.	Needs real-world implementation case studies to assess impact on mission-critical operations.
Mohammadi and Rezaei [11]	Bayesian Best-Worst Method (BWM)	Group Decision-Making	Introduced probabilistic BWM for stable, confidence-based weight estimation; improved consensus.	Requires testing in multi-stakeholder environments and integration with dynamic data models.
Cheraghalipour *et al.* [12] and Saner *et al.* [13]	BWM + Fuzzy-VIKOR	Construction Projects	Provided a contractor evaluation model with compromise ranking under fuzziness.	Needs wider application and benchmarking with other contractor evaluation models.
Wang *et al.* [14]	Fuzzy AHP + PROMETHEE II	Textile Industry (Vietnam)	Hybrid model integrating SCOR framework; assessed qualitative and quantitative supplier data.	Limited to textile industry; lacks comparisons with other MCDM frameworks and real-time data use.
Vardin *et al.* [15]	BWM + Fuzzy-VIKOR	Construction (Water Projects)	Case-validated model for contractor selection; outperformed lowest-bid method.	Model not applied in live tender systems; comparison with other models suggested for future work.
Javad *et al.* [16]	BWM (Best–Worst Method) + Fuzzy TOPSIS	Steel industry (green supplier selection)	Developed a green-supplier selection framework for a steel-company case, identifying key criteria and ranking suppliers based on green innovation.	Limited to one company/context; broader generalization, comparison with other MCDM methods, and dynamic/real-time data integration remain under-explored.

The above approaches use various decision making frameworks and methods for supplier selection.

A summary of these approaches is given in Table I that provides most relevant studies.

III. RESEARCH METHODOLOGY

A. Methodology Framework

This study aims to evaluate and rank suppliers for an EPC based organization which focuses on selecting suitable suppliers for the engineering and construction projects carried out by them.

This involves 5 phases of evaluation on a broader level, which is represented in the Fig. 1. In the first phase the key criteria to be used for supplier selection are determined by using a key criteria identification questionnaire form circulated among the decision makers. In the second phase weightage are assigned to the criteria based on the best and worst criteria evaluation and incorporating uncertainty in determining the same. In the third phase, plausibility values assigned for each criteria and ranking probabilities were assigned for criteria based on its rank value. In the fourth phase, the decision matrix is obtained based on the expert's preference score for each supplier against each criteria selected in the first phase. The supplier performance score is obtained using the fuzzy VIKOR method and fuzzy TOPSIS method. In the fifth phase, the criteria weightage, criteria ranking probability score are combined together along with decision maker's preference score for each supplier to determine the final supplier score using fuzzy VIKOR method and fuzzy TOPSIS under uncertainty. The supplier scores obtained with the two methods are compared to obtain stable results.

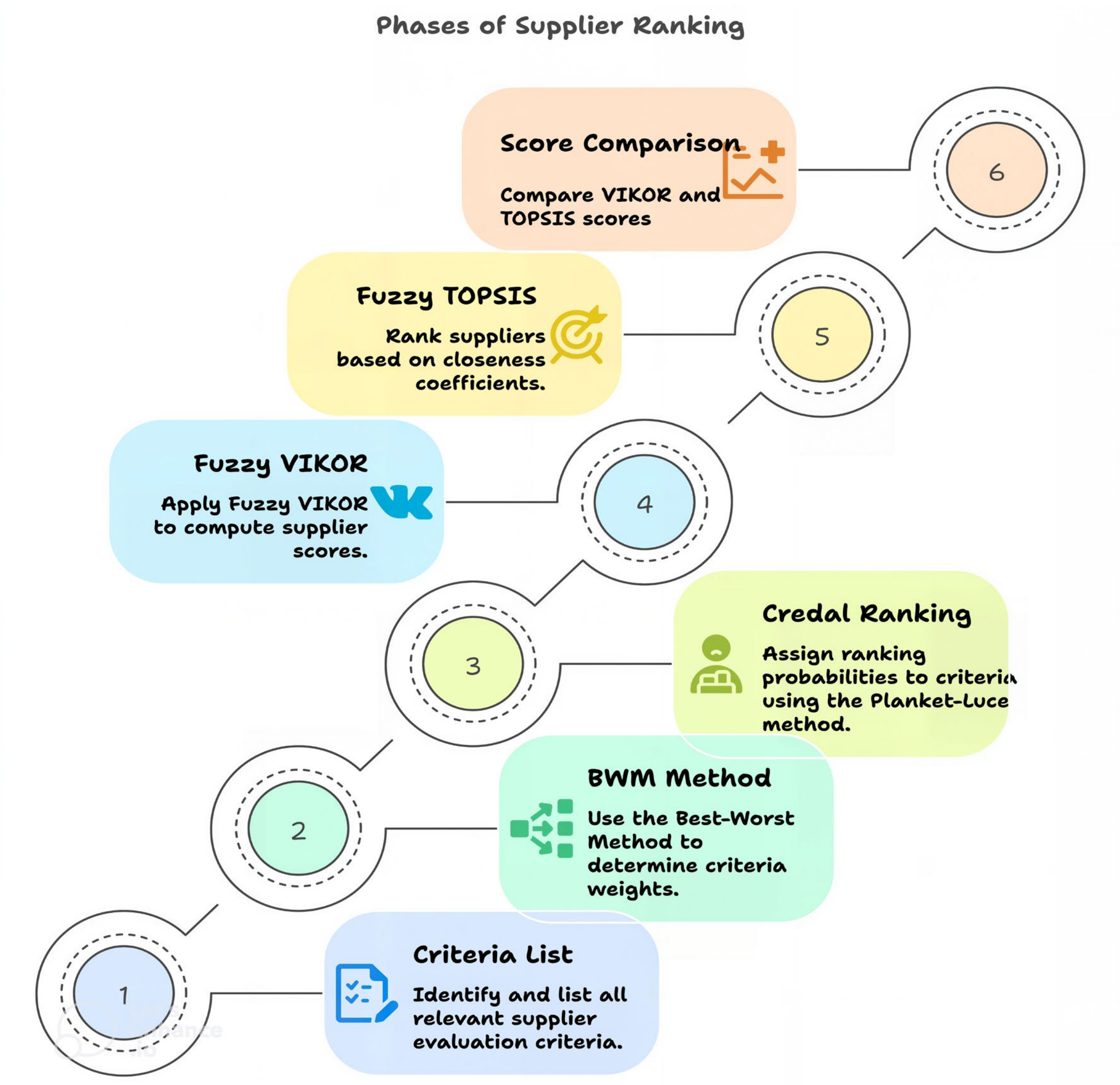

Fig. 1. Phases of supplier evaluation.

The results were presented as definitive insights for managerial comprehension and included recommendations for directing future research efforts.

B. Relevant Criteria for Supplier Selection

In EPC projects, supplier selection is crucial as it directly influences project cost, quality, and timelines. Apart from these criteria, modern procurement industries are demanding integration of environmental impact assessments to reduce emissions and ecological harm, sustainability criteria such as efficiency, waste reduction, and circular economy for an effective supplier evaluation. Simultaneously, ethical concerns like fair labor and human rights protection are gaining importance as stakeholders demand greater accountability. Together, these dimensions align procurement with global Environmental, Social, and Governance standards, fostering responsible and resilient supply chains.

Choosing the right suppliers ensures reliable material procurement and smooth execution across all project phases. Careful culling of the available literature and to shortlist the important criteria set for supplier selection in procurement operations within an industrial EPC context, involves the expertise of the key decision makers with experience in procurement operations. The development of ideal selection criteria was based on a comprehensive literature review. The result of these efforts is shown in Fig. 2, which provides a well-structured and perceptive summary of the various criteria that are been considered for selection of a supplier in the procurement industry.

The major decision makers of the engineering industry are asked to rate the criteria by providing a ranking scale between 1–10 and the top highly ranked 12 criteria is selected which involves quality, cost, delivery, environmental impact, sustainability aspects, since they are the key considerations for selecting suppliers. They are further been used for internal criteria weight calculation and subsequent ranking of suppliers using MCDM approaches.

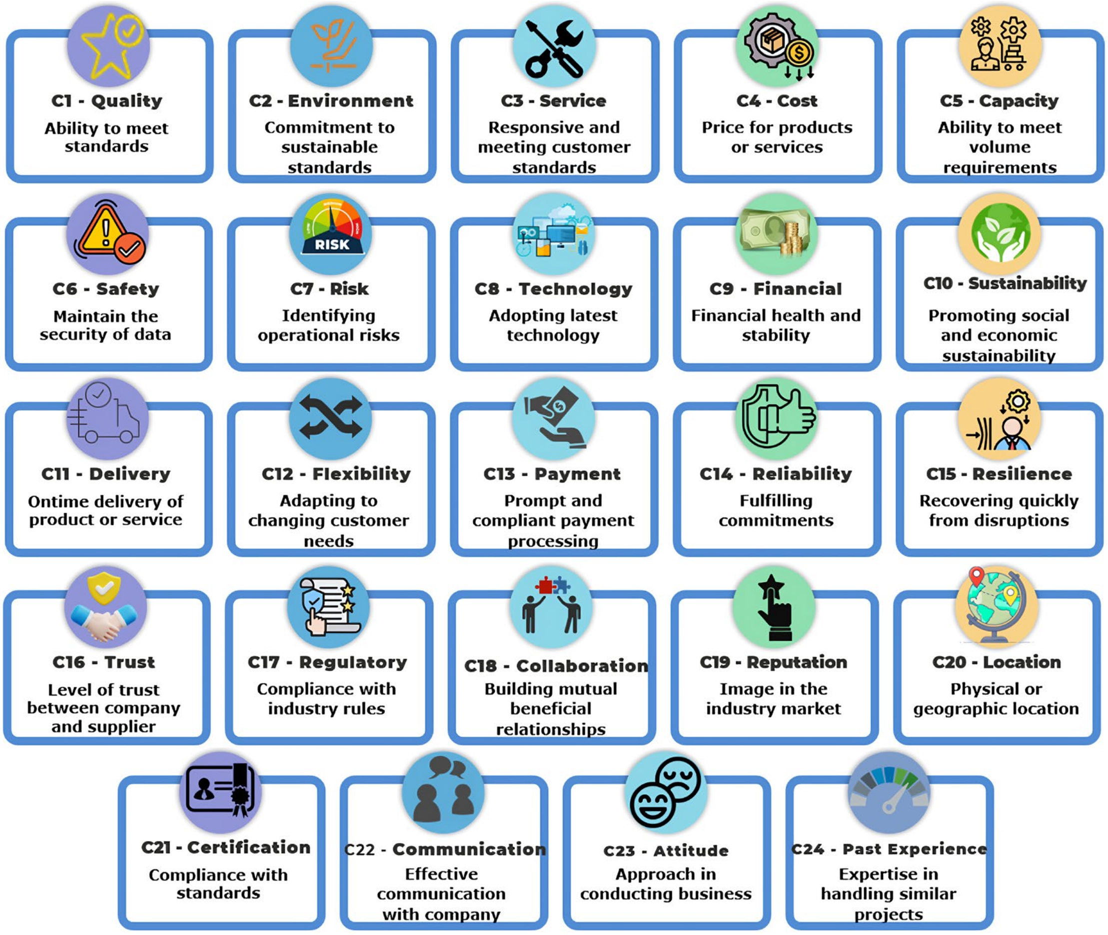

Fig. 2. Ideal supplier selection criteria list.

C. Bayesian Best-Worst Method

Razaei [17] first proposed the Best-Worst Method (BWM) to address decision-making issues. It finds the optimal option from a group of options by taking a set of criteria into account, and it's based on the idea of Multi-Criteria Decision-Making (MCDM).

The best-worst approach is depicted as follows:

Step 1: Specify the set of decision criteria, in order to determine the Criteria Set (CS) = $\{CR_1, CR_2 \ldots CR_n\}$ which are considered for taking the final decision

Step 2: Decision Maker (DM) has to determine the best-most important criteria CR_{bm} and the worst, least preferred criteria CR_{wl}.

Step 3: The best-most-important criterion, CR_{bm}, and other criteria from CS are compared pairwise by DM to provide his/ her preference scale in the range of 1–9.

The scale value is obtained based on the values given in Table II below.

TABLE II. PAIRWISE COMPARISON FOR CRITERIA ASSESSMENT

Degree of Importance	Linguistic Terms
1	Equally Important (EI)
3	Weakly Important (WI)
5	Fairly Important (FI)
7	Very Important (VI)
9	Absolutely Important (AI)
2, 4, 6, 8 can be used to express Intermediate values	

A scale value of 1 denotes the selected best-most important criteria (CR_{bm}) is of equal importance to the other criteria under consideration and 9 denotes that the selected best-most important critera (CR_{bm}) is highly important compared to the other criteria under consideration.

The preference of the best criteria over the other criteria vector is given using a number from 1 to 9 to form the vector of the Best-to-Others (BO) represented in Eq. (1).

$$A_{bm} = (a_{bm1}, a_{bm2} \ldots a_{bmn}) \quad (1)$$

where a_{bm1}, a_{bm2}, a_{bmn} are the sequence of preference values with respect to the best-most important criterion (CR_{bm}), considering the set of criteria given in the Criteria Set (CS).

Step 4: The Decision maker compares each of the other criteria to the worst criterion CR_{wl} and gives a value that shows how much each of the other criteria is better than the worst criterion.

The resulting other criteria-to-Worst vector is represented in Eq. (2).

$$A_{wl} = (a_{wl1}, a_{wl2} \ldots a_{wln}) \quad (2)$$

where $a_{wl1}, a_{wl2}, a_{wln}$ are the sequences of values which represents the importance of various criteria relative to the least worst important criterion CR_{wl}.

Step 5: Determine Optimal Weights (OW_1, OW_2, ..., OW_n).

The optimal weight for the criteria is the one where for each pair $\frac{OW_{bm}}{OW_j} = \alpha_{bmj}$ and $\frac{OW_j}{OW_{wl}} = \alpha_{jwl}$.

Solve the Eq. (3) and Eq. (4), such that the value of ε is minimum and the sum of the optimal weights is equal to 1 as given in Eq. (5).

$$\left|\frac{OW_{bm}}{OW_j} - \alpha_{bmj}\right| \leq \varepsilon \text{ for } j = 1, 2, 3...n \tag{3}$$

$$\left|\frac{OW_j}{OW_{wl}} - \alpha_{jwl}\right| \leq \varepsilon \text{ for } j = 1, 2, 3...n \tag{4}$$

$$\sum_{j=1}^{n} OW_j = 1 \;\; W_j \geq 0 \text{ for } j = 1, 2, 3...n \tag{5}$$

where,
OW_{bm}—the weight of the best criterion.
OW_j—the weight of each criterion.
OW_{wl}—the weight of worst criterion.
α_{bmj}—the Best-to-others comparison value, which shows how important the best criterion is compared to each criterion, as given by the expert.
α_{jwl}—the other-to-worst comparison value, which shows how important each criterion is compared to the worst criterion as given by the expert.
ε—the maximum deviation that the model minimizes to achieve a consistent weight set.

Resolving the model as mentioned earlier yields the optimal weights for each criterion, where the sum of the optimal weights is equal to 1 as given in Eq. (5).

Step 6: Bayesian Best-Worst Method (BWM): In order to handle the uncertainty and variability in expert judgments performed by the decision makers, the Bayesian BWM method is used [11]. The Analytical Bayesian BWM using Dirichlet aggregation is used to identify the criteria weights under uncertainty. In this analytical method, expert-provided Best-to-Others (BO) and Others-to-Worst (OW) vectors are transformed into pairwise comparison constraints, and weights are modeled using a Dirichlet distribution. The aggregation across multiple experts is performed analytically by updating the Dirichlet parameters based on expert inputs, enabling efficient and fast computation of the expected weight vector without sampling. This approach is ideal for large-scale or time-sensitive applications due to its computational simplicity.

D. Credal Ranking Probability

Credal ranking probabilities represent degrees of belief in the ranking of alternatives (e.g., suppliers) [11], especially when uncertainty or imprecision is involved. When integrated with Bayesian BWM weights, they allow for robust, uncertainty-aware decision-making. Each criteria is associated with a probability value indicating how likely it is to occupy a particular rank. The Plackett-Luce (PL) model is a popular probabilistic ranking model used to model the likelihood of a particular ranking over a set of alternatives or items such as criteria.

Based on the Criteria Set $CS = (CR_1,\ CR_2\ ...\ CR_n)$ and Ranking $\pi = (CR_{\pi 1}, CR_{\pi 2} ... CR_{\pi n})$ the probability of ranking under the Plackett–Luce (PL) Probability model is represented in Eq. (6).

$$P(\pi) = \prod_{k=1}^{n} \frac{W_{CR_{\pi k}}}{\sum_{j=k}^{n} W_{CR_{\pi j}}} \tag{6}$$

where,
π—ranking permutation of items.
π_k—the item in position k.
$CR_{\pi k}$—item ranked at position k in the permutation π.
$W_{CR_{\pi k}}$—Positive worth parameter which represents items' importance or utility.
$\sum_{j=k}^{n} W_{CR_{\pi j}}$—sum of the worth parameters of items used for Normalization.
$P(\pi)$—Probability of observing the ranking π.

This ensures that ranking with higher BWM weights will have a high probability. The credal ranking probability is aggregated for each criterion, taking into account the probability of a criterion at each ranking position by using Eq. (7).

$$S_i = \sum_{k=1}^{n} (n - k + 1) + P_{i,k} \tag{7}$$

where,
S_i—raw weight of Criterion C_i.
$P_{i,k}$—probability of CR_i appearing in the rank position k.
n—Total number of criteria.
k—Rank position index (i.e., 1st, 2nd … nth).

The multiplier ($n-k+1$) ensures that higher rankings contribute more.

The probability score is normalized for each criterion such that the total score accounts for a sum of 1, using Eq. (8).

$$P_i^{final} = \frac{S_i}{\sum_{j=1}^{n} S_j} \tag{8}$$

where, S_i is the raw weight of the criterion, S_j is total sum of all criteria's scores and P_i^{final} is the final probability score for each criterion i.

Finally, the probability of each criterion occupying a specific rank position is computed by aggregating the probabilities of all rankings in which that criterion appears in the corresponding position. The final credal ranking probability reflects both the expert judgements using Bayesian BWM and ranking uncertainty.

Credal ranking addresses two core weaknesses of BWM and fuzzy VIKOR/TOPSIS by replacing single-point inputs and outputs with credal sets—interval-valued probabilities that explicitly encode epistemic uncertainty from incomplete or conflicting evidence.

First, BWM relies on expert pairwise comparisons and consistency thresholds; despite improvements, judgments can still be subjective and inconsistently specified, whereas credal models propagate ranges of plausible weights instead of committing to a single vector, yielding decisions only when dominance holds for all compatible distributions. Second, when the evidence is insufficient, credal dominance returns lower-upper support for each alternative, producing partial orders and incorporating sensitivity without ad hoc defuzzification choices. Fuzzy VIKOR/TOPSIS also requires defuzzification and fixed distance metrics that can bias rankings and be sensitive to fluctuations or rank reversal.

E. Fuzzy VIKOR

VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), a compromise ranking technique for multi-criteria decision-making described by Taherdoost *et al.* [18], is used as the basis for identifying the best option, when there are conflicting criteria. It also aids in identifying the best option by ranking the list of options in ascending order.

Step 1: In this step, the fuzzy VIKOR method identifies the linguistic variables, which are qualitative terms or phrases from a natural language that represent an expert's subjective perspective regarding the criteria applied to each alternative being evaluated. The triangular fuzzy numbers, as shown in Table III, are used to give the evaluation scale for each alternative with respect to each criterion.

TABLE III. LINGUISTIC TERMS OF TRIANGULAR FUZZY NUMBERS

Triangular Fuzzy Number	Linguistic Terms
(0, 1, 2)	Very Poor (VP)
(1, 2, 3)	Poor (P)
(2, 3, 4)	Moderately Poor (MP)
(3, 5, 7)	Fair (F)
(5, 7, 9)	Moderately Good (MG)
(7, 8, 9)	Good (G)
(8, 9, 10)	Very Good (VG)

Step 2: Formation of the fuzzy Decision matrix. Consider a group of k decision makers (DM_1, DM_2, …, DM_k) presented with m Alternatives (AL_1, AL_2, …, AL_m) against n criteria (CR_1, CR_2, …, CR_n). The alternatives AL_1, AL_2, …, AL_m is represented as rows and CR_1, CR_2, …, CR_n is represented as columns for the following matrix Eq. (9).

$$\begin{matrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ x_{m1} & x_{m2} & x_{mn} \end{matrix} \tag{9}$$

where in $\boldsymbol{x_{mn}}$ is the rating of Alternatives $\boldsymbol{AL_m}$ with respect to the criterion CR_j.

The value $X_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is the Triangular Fuzzy Number (TFN) value corresponding to the preference of an alternative with respect to a criteria CR_j by the Decision Maker (DM).

Step 3: The graded integration method is employed to consolidate the perspectives of all decision makers, considering the evaluations of the alternatives

This is represented as $X_{ij}^k = (l_{ij}^k, m_{ij}^k U_{ij}^k)$, and was calculated as Eq. (10).

$$l_{ij} = min_k\{l_{ij}^k\};\ m_{ij} = \frac{1}{K}\sum_{k=1}^{k} m_{ij}^k\ ;\ u_{ij} = max_k\{u_{ij}^k\} \tag{10}$$

where l, m, u are the lower, middle, and upper values of TFN for each alternative represented by i against each criterion j from k number of decision makers as give n in Eq. (10).

Step 4: Determine the best value fb_i^+ and worst value fb_i^- where are represented as fuzzy values using Eq. (11) for benefit criteria and Eq. (12) for cost criteria.

$$fb_i^+ = max_i\, f_{ij} \text{ and } fb_i^- = min_i\, f_{ij} \tag{11}$$

$$fb_i^+ = min_i\, f_{ij} \text{ and } fb_i^- = max_i\, f_{ij} \tag{12}$$

where f_{ij} is the aggregated fuzzy ratings of each alternative i, against each criterion j.

Step 5: Computing utility measure (SU_i) and regret measure (RM_i) values by Eqs. (13)–(14).

$$SU_i = \sum_{j=1}^{n} WC_j\,(fb_j^+ - f_{ij})/(fb_j^+ - fb_j^-) \tag{13}$$

$$RM_i = max[WC_j(fb_j^+ - f_{ij})/(fb_j^+ - fb_j^-)] \tag{14}$$

where,
WC_j—the criterion weight.
fb_i^+—best fuzzy value.
fb_i^-— worst fuzzy value.
f_{ij}—the aggregated fuzzy ratings of each alternative.

Step 6: Compute the Q_i compromise values using Eq. (15).

$$Q_i = v \times \frac{(SU_i - SU^*)}{(SU^- - SU^*)} + (1 - v) \times \frac{(RM_i - RM^*)}{(RM^- - RM^*)} \tag{15}$$

where,
$SU^* = min_i SU_i$.
$SU^- = max_i SU_i$.
$RM^* = min_i RM_i$.
$RM^- = max_i\, RM_i$.
v −decision making strategy weight usually taken as 0.5.

VIKOR scores (Q values) are based on group satisfaction and individual regret. Sorting the Q score in ascending determines the ranking of the alternatives.

F. Fuzzy TOPSIS

The Fuzzy TOPSIS is an improved MCDM technique, which is a extension of TOPSIS method that incorporates fuzzy set theory to handle uncertainty and vagueness in decision-making. It evaluates alternatives by measuring their distance from the fuzzy positive ideal solution and fuzzy negative ideal solution.

Step 1: This step involves the formation of the fuzzy decision matrix with *m* alternatives represented as rows and *n* criteria represented as columns and its represented as in Eq. (16).

$$X = \begin{matrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ x_{m1} & x_{m2} & x_{mn} \end{matrix} \tag{16}$$

Step 2: Determine the normalized decision matrix. The normalized values r_{ij} is calculated using min-max normalization equation as given in Eq. (17) for benefit criteria and Eq. (18) for cost criteria.

$$r_{ij} = \frac{x_{ij} - min_j\,(x_{ij})}{max_j\,(x_{ij}) - min_j\,(x_{ij})} \tag{17}$$

$$r_{ij} = \frac{max_j\,(x_{ij}) - x_{ij}}{max_j(x_{ij}) - min_j(x_{ij})} \tag{18}$$

where,
x_{ij}—original performance value of alternative i under criterion j.

$min_j\ (x_{ij})$—minimum value of criterion j among all alternatives.
$max_j\ (x_{ij})$—maximum value of criterion j among all alternatives.
r_{ij}—normalized value (after scaling to [0, 1]).

Step 3: Calculate the weighted normalized decision matrix v_{ij} according to Eq. (19).

$$v_{ij} = w_i \times r_{ij} \tag{19}$$

where,
w_i—weight of the criterion i.
r_{ij}—is the min-max based normalization value obtained from Eqs. (17)–(18).

Step 4: Calculate Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) vectors using Eq. (20) and Eq. (21), respectively.

$$\text{PIS: } V_j^+ = \{max_j\ (v_{ij})\} \tag{20}$$

$$\text{NIS: } V_j^- = \{min_j\ (v_{ij})\} \tag{21}$$

where,
v_{ij} —weighted normalized value of alternative i for criterion j.
V_j^+—best ideal value for criterion j.
V_j^-—worst anti-ideal value for criterion j.

Step 5: calculate Euclidean distance measure to determine how far each alternative (i.e., supplier i) is from the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS) using Eqs. (22)–(23).

$$Dt_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \tag{22}$$

$$Dt_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \tag{23}$$

where,
Dt_i^+—Distance of alternative i from the ideal best solution.
Dt_i^-—Distance of alternative i from the anti ideal worst solution.
v_{ij} —weighted normalized value of alternative i on criterion j.
v_j^+—best ideal value for criterion j.
v_j^-—best anti-ideal value for criterion j.
n—Total number of criterion.

Step 6: Calculate the closeness coefficient using the Eq. (24).

$$CC_i = \frac{Dt_i^-}{Dt_i^- + Dt_i^+} \tag{24}$$

where,
CC_i—Closeness coefficient.
Dt_i^+—Distance of alternative i from the ideal best solution.
Dt_i^-—Distance of alternative i from the anti ideal worst solution.

This value is always between 0 and 1, and the alternatives that gets closer to 1 would be better.

G. Hybrid Approach for Supplier Ranking

The Q-values derived from the Fuzzy VIKOR technique, which represent the compromise ranking of alternatives, is calculated by taking into account both the Bayesian BWM weights and the credal ranking probabilities of the criteria in order to arrive at the final overall score for each supplier The posterior criteria weights used for calculating the Q-Score is modulated by using Bayesian BWM, which indicate the relative relevance of each criterion and by using credal ranking probability which indicates the degree of belief or confidence. Thus, a robust, uncertainty-aware final score for rating the suppliers is produced by combining performance (from VIKOR), relevance (from BWM), and epistemic confidence (from credal probabilities).

The final overall supplier score F_i for i^{th} supplier can be calculated as Eq. (25).

$$F_i = \sum_{j=1}^{m} WC_j \times Q_i \tag{25}$$

where,
WC_j—cumulative weight of a criterion calculated using Bayesian BWM and credal ranking.
Q_i —Q Score of i^{th} supplier calculated based on the Bayesian BWM and credal ranking probability value using VIKOR.

Similarly, the closeness coefficient scores calculated by using fuzzy TOPSIS is calculated by using the weights of the criteria determined by the Bayesian BWM method and the credal ranking probabilities in order to arrive at the overall score for each supplier. In case of TOPSIS, higher coefficient value means the better alternative; hence the scores are sorted in descending order to rank the suppliers.

The final overall supplier score F_i for i^{th} supplier can be calculated as Eq. (26).

$$F_i = \sum_{j=1}^{m} WC_j \times CC_i \tag{26}$$

where,
WC_j—cumulative weight of a criteria calculated using Bayesian BWM and credal ranking.
CC_i—Closeness Coeeficient (CC) Score of i^{th} supplier calculated based on the Bayesian BWM and credal ranking probability value using TOPSIS.

IV. CASE STUDY

The major difficulties an EPC business has in identifying appropriate suppliers that can satisfy its operational and performance compliance needs. The organization recognizes the importance of obtaining supplies for the procurement of materials essential for construction projects that are reliable and meet delivery specifications to ensure project completion. The business highlights the significance of resilience when confronted with unexpected events that may disrupt supply chain operations. Identifying suppliers that meet operational and compliance standards is a major challenge, especially in a dynamic market with many options and evolving procurement policies. Companies must also consider the diverse expectations of stakeholders and customers during supplier selection. Operational integrity ensures consistent product quality and reliability, while delivery compliance supports production timelines and minimizes disruptions. Reliable suppliers improve logistics, reduce costs, and enhance market responsiveness. Strong performance in both areas is essential for meeting customer needs and maintaining competitiveness.

In today's fast-changing business environment, suppliers must adapt to new technologies to stay competitive and meet evolving client demands. Those using advanced systems and automation can offer greater efficiency, quality, and speed. A supplier's track record also reflects reliability and domain expertise. However, organizations must balance these strengths with budget constraints, as high-cost suppliers may affect project viability. Thus, choosing suppliers involves weighing innovation, experience, and cost-effectiveness. Given these complex criteria, identifying suitable, timely, and operationally capable suppliers remains a challenge. To address this, the study proposes a comprehensive framework that evaluates delivery performance, specification integrity, risk preparedness, and technological advancement to support strategic business goals.

In the latest scenario of Industry 4.0, suppliers are expected to comply with environmental regulations, sustainability standards and legal practices which helps organization to avoid supply chain disruptions caused by non-compliance. Also, this can be inspected by means of certifications obtained by the suppliers that gives an indication that they adhere to the ethical and sustainability standards, in turn enhance brans reputation and aligning to procurement with global ESG goals.

A. Identifying Relevant Criteria and Bayesian Weight Assignment

A thorough list of criteria was developed from pertinent literature in order to determine the optimum criterion for choosing the finest engineering provider. Experts were then shown a criteria list (Fig. 2), and they were asked to select the best criteria that were particularly relevant to engineering and procurement operations. As a result, a final set of 12 criteria represented in Fig. 3 were carefully selected for efficient identification of suitable suppliers for an engineering project.

Fig. 3. Identified criteria list-procurement industry.

After identifying high-priority criteria as illustrated in Fig. 3, survey forms were developed to facilitate a comparative assessment of these criteria using the numerical values supplied by experts. The list of key experts provided in Table IV, gave their preference and weightage by using the scale value given in Table II.

TABLE IV. Decision Makers-Relevant Work Experience

Expert	Position	Years of Experience
1	Managing Director-Procurement Company	32
2	Deputy General Manager	28
3	General Manager	25
4	Senior Procurement Engineer	22
5	Senior Engineer	20

The criteria weights are determined using the Analytical Bayesian BWM-Dirichlet aggregation using Eqs. (1)–(5). The best-to-other criteria pairwise comparison were provided by the experts and are represented in Table V (C1–C6), and Table VI (C7–C12) using Bayesian BWM-Dirichlet mean method. The pairwise comparison which determines the preference of other criteria over the worst criteria is given in Table VII.

After the experts' fill in the survey forms based on their expertise and domain experience, the comparative weights assigned to each criterion using the Dirichlet Mean, are given in Table VIII. As five experts participated in this study, the final weights were determined by combining their perspectives. The final aggregated weight was determined by averaging the weights of each expert's assessments. The Analytical Bayesian BWM uses Dirichlet aggregation to provide the comparative weights for each criterion as a single weight set with faster computation time and gives precise values.

TABLE V. Pairwise Comparison of Best Important Criteria-to-Other Criteria (C1–C6)

Criteria		Quality	Service	Delivery	Cost	Capacity	Technology
Expert	Best Criteria	C1	C2	C3	C4	C5	C6
1	1	1	2	2	7	5	8
2	2	2	1	3	6	6	7
3	3	3	2	1	5	7	7
4	10	2	3	4	5	7	8
5	11	3	2	2	3	5	6

TABLE VI. Pairwise Comparison of best Important criteria-to-Other Criteria (C7–C12)

Criteria		Reliability	Risk	Past Experience	Environment	Sustainability	Regulation
Expert	Best Criteria	C7	C8	C9	C10	C11	C12
1	1	5	3	9	6	7	9
2	2	5	8	4	6	6	5
3	3	6	4	2	6	3	7
4	10	5	6	7	1	5	9
5	11	8	9	4	5	1	3

TABLE VII. PAIRWISE COMPARISON OF OTHER CRITERIA-TO-WORST CRITERIA

Expert	1	2	3	4	5
Worst Criteria	Reliability	Capacity	Technology	Risk	Past Experience
	C7	C5	C6	C8	C9
C1	9	8	9	9	8
C2	8	9	9	8	9
C3	8	8	7	7	6
C4	5	7	7	7	5
C5	5	1	6	5	5
C6	4	4	1	4	4
C7	1	3	3	3	2
C8	2	3	3	1	3
C9	2	3	2	3	1
C10	6	5	3	4	2
C11	7	8	6	3	3
C12	4	7	9	6	3

TABLE VIII. GREGATED CRITERIA WEIGHT USING DIRICHLET MEAN

Criteria	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	CR_8	CR_9	CR_{10}	CR_{11}	CR_{12}
Weight	0.1825	0.1833	0.1550	0.1008	0.0359	0.0237	0.0281	0.0331	0.0343	0.0644	0.0873	0.0717

The Final aggregated weights as given in Table VIII, which uses Analytical Bayesian BWM with Dirichlet aggregation, have been considered for further calculations.

B. Credal Ranking Probability Assignment for Criterion

Credal ranking is a decision-making approach that assigns a set of plausible rankings to alternatives based on imprecise or interval-valued criteria weights. The process of deriving credal ranking probabilities begins by defining all possible rankings of the given criteria. Once the set of all possible rank permutations is established, plausibility values are assigned to each ranking based on available information, expert judgment, or uncertainty modeling. These plausibility values are then converted into probability distributions.

The criteria weights obtained above have been used to find the credal ranking and provide a graph based on the probability distribution for each criteria, which is given in Fig. 4. The network graph represents the credal ranking relationships among supplier selection criteria derived from Bayesian BWM weights. Each directed edge indicates the probability that one criterion is preferred over another, with stronger weights showing higher dominance.

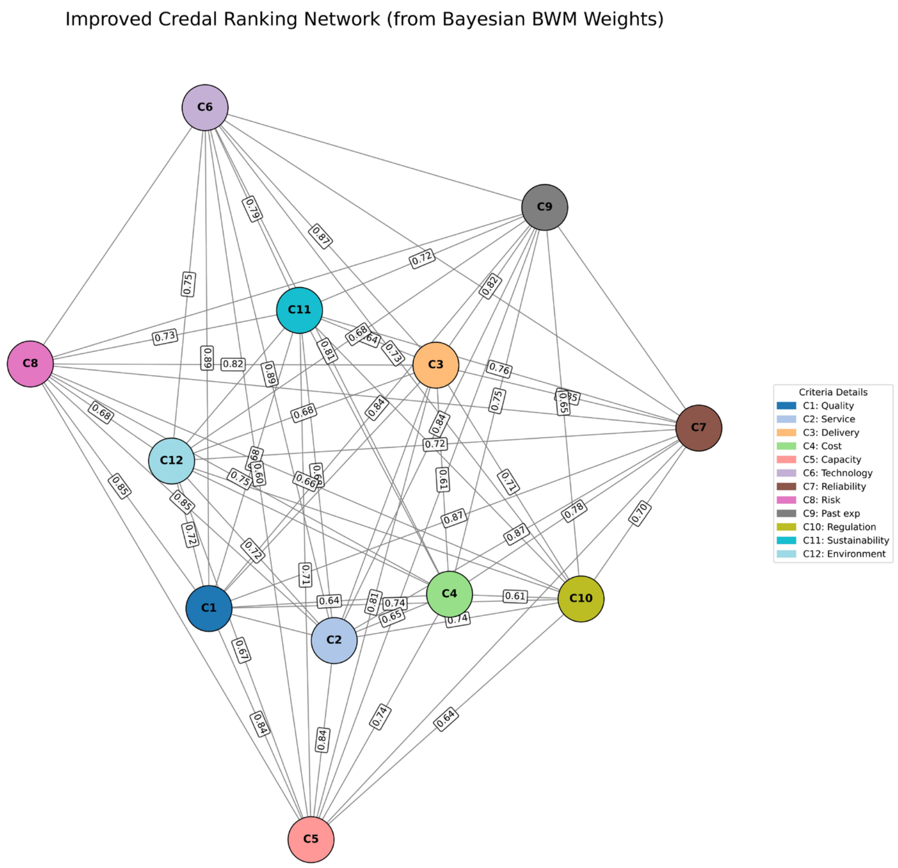

Fig. 4. Credal ranking visualization.

The graph maps interdependencies among 12 supplier-selection criteria using Bayesian BWM-derived strengths; thicker edges denote stronger influence. Risk, Regulation, and Capacity appear as high-centrality nodes, exerting broad influence across the network, indicating systemic leverage points. Delivery, Service, and Quality form a tightly connected core, suggesting operational performance criteria co-move and jointly propagate effects.

The edges with weights above 0.5 are treated as "high-confidence" preferences and edges with weight range between 0.45 to 0.49 have to be considered next in preference and edges with less than 0.20 are treated as low-confidence preferences. There are some strongest edges which indicates strong and high confidence pairwise preferences. The weight between Regulation and Reliability is 0.70 in the graph, signaling robust precedence of Regulation over Reliability in pairwise ordering. Similarly, the weight between Service and Delivery is 0.72, the most prominent central edge, suggesting Service decisively outranks Delivery among core operational criteria

The probability distribution of each criteria at each position is further normalized and aggregated to generate a single probability value for each criteria. The final probability Score P_i for each criteria is given in Table IX.

TABLE IX. FINAL CRITERIA WISE-PROBABILITY SCORE

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Probability Score	0.1176	0.1176	0.1122	0.0965	0.0934	0.0875	0.0831	0.0633	0.0614	0.0614	0.0560	0.0501

The ranking probabilities are taken as input along with Bayesian criteria weights to find the final supplier ranking using MCDM models like fuzzy VIKOR and fuzzy TOPSIS.

C. Integrating BWM Credal Ranking Probabilities with VIKOR & TOPSIS Score for Supplier Ranking

The Fuzzy VIKOR method is used to obtain the preference of each supplier by the decision makers. To initiate the assessment process, a decision matrix is formed based on opinions obtained from the experts as per the given in Table II. The Survey forms was circulated to the decision makers given in Table IV who are involved in the decision making process of supplier selection. The experts were requested to evaluate five suppliers of the EPC company using the fuzzy language variables given in Table III and outcome of the preferences with respect to each of the twelve shortlisted criteria against the five suppliers is outlined Tables X and XI. The ratings of the suppliers are given as dynamic inputs by means of linguistic variables and are then normalized to generate the decision matrix. The dynamically generated decision matrix is given as input to the MCDM approaches such as fuzzy VIKOR and fuzzy TOPSIS. To maintain confidentiality, the names of the suppliers have been omitted and letter A to E are used for identification purposes.

TABLE X. DECISION MATRIX FOR CRITERIA 1–6

Criteria	Supplier	Expert-Decision Maker				
		1	2	3	4	5
Quality	A	G	G	G	G	G
	B	F	F	F	F	F
	C	VG	VG	VG	VG	VG
	D	P	P	P	P	P
	E	MG	MG	G	MG	MG
Service	A	F	MG	F	MG	F
	B	P	F	F	F	P
	C	G	G	G	G	G
	D	MP	MP	F	MP	MP
	E	G	G	G	G	G
Delivery	A	P	F	F	P	P
	B	MP	MP	MP	MP	MP
	C	F	MG	F	F	F
	D	F	F	F	F	F
	E	G	G	G	G	G
Cost	A	VG	VG	VG	VG	VG
	B	G	G	G	G	G
	C	F	F	F	F	F
	D	P	P	P	P	P
	E	G	G	G	G	G
Capacity	A	G	G	G	G	G
	B	F	F	F	F	F
	C	G	G	G	G	G
	D	F	F	F	F	F
	E	VG	VG	VG	VG	VG
Technology	A	F	F	MG	F	F
	B	P	MP	F	P	P
	C	F	F	F	F	F
	D	MP	MP	MP	MP	MP
	E	MG	G	G	MG	MG

TABLE XI. DECISION MATRIX FOR CRITERIA 7–12

Criteria	Supplier	Expert-Decision Maker				
		1	2	3	4	5
Reliability	A	P	P	F	P	P
	B	F	F	F	F	F
	C	MG	G	MG	MG	MG
	D	P	P	P	P	P
	E	F	F	F	F	F
Risk	A	G	G	G	G	G
	B	MG	MG	G	MG	MG
	C	VG	VG	VG	VG	VG
	D	P	P	P	P	P
	E	G	G	G	G	G
Experience	A	F	F	F	MG	F
	B	G	G	G	G	G
	C	F	F	F	F	F
	D	MP	F	MP	P	MP
	E	G	G	G	G	G
Regulation	A	G	MG	F	P	F
	B	MG	F	MG	MG	MG
	C	MG	MG	MG	F	P
	D	MG	MG	MG	MG	MG
	E	G	MG	F	P	P
Sustainability	A	VG	G	MG	MG	G
	B	G	MG	VG	VG	VG
	C	VG	VG	G	MG	MG
	D	G	G	VG	G	G
	E	G	G	G	MG	MG
Environment	A	F	P	G	G	G
	B	P	G	F	F	F
	C	F	F	P	G	G
	D	G	P	F	P	P
	E	G	P	G	G	G

A strong hybrid method for evaluating suppliers is provided by combining VIKOR rankings with Bayesian BWM credal ranking probability. By using probabilistic scores to describe the degree of belief in the significance of each criterion, the credal ranking from Bayesian BWM captures the subjective uncertainty in expert preferences.

The VIKOR approach, emphasizes compromise solutions based on individual regret and collective utility, concentrating on the objective performance of alternatives. Decision-makers can more effectively account for the fluctuation of expert judgement and quantitative alternative performance by combining these two viewpoints, which will result in supplier rankings that are more resilient and well-informed. This combination promotes more assured, risk-aware decision-making and increases transparency.

D. *Results of VIKOR & TOPSIS Approach*

The final VIKOR Q score is then determined by applying the Bayesian BWM aggregated weight, credal probability score, and group utility and individual regret to the decision matrix results. The resulting Q Score is used to rank the suppliers as given in Table XII and the supplier rating based on scores is given in Fig. 5.

TABLE XII. FINAL SUPPLIER RANKING-VIKOR METHOD

Supplier	Group Utility	Individual Regret	Q Score	Rank
A	0.042708	0.017288	0.6084	3
B	0.059334	0.021389	0.8694	4
C	0.015188	0.004564	0.0101	1
D	0.074935	0.021311	0.9976	5
E	0.015601	0.005500	0.0312	2

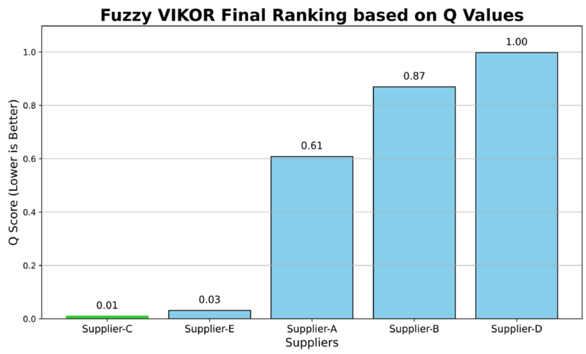

Fig. 5. Final supplier ranking using VIKOR.

The sensitivity analysis on the supplier Q score for the five suppliers (A–E) using the hybrid VIKOR method is given in Fig. 6. The sensitivity analysis based on Q Score for each supplier across 100 simulation runs with varied criteria weights. According to the Y-axis, a lower Q Score indicates a better performance. The green line (C) purple line (E) constantly remain at the bottom of the chart. This indicates that the suppliers C and E are consistently best performers. Their high ranking is robust and not significantly affected by changes in the importance of different criteria.

The same decision matrix given in Tables X and XI is used to evaluate the suppliers using the TOPSIS method by using Bayesian BWM weights along with the credal ranking probability score. The final closeness coefficient score calculated is given in Table XIII, which is used to rank the alternatives based on their closeness to the ideal solution and their distance from the negative ideal solution. The alternative with the highest coefficient is ranked first and in given Fig. 7.

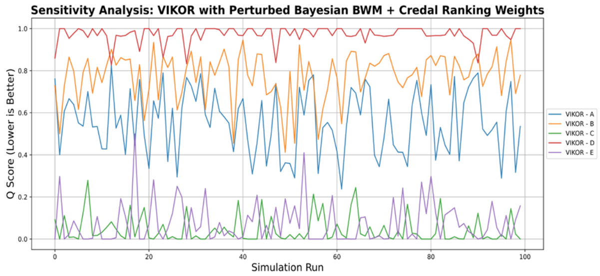

Fig. 6. Sensitivity analysis of VIKOR.

TABLE XIII. FINAL SUPPLIER RANKING USING TOPSIS

Supplier	Closeness Coefficient Score	Rank
A	0.5934	3
B	0.4439	4
C	0.8399	2
D	0.2271	5
E	0.8454	1

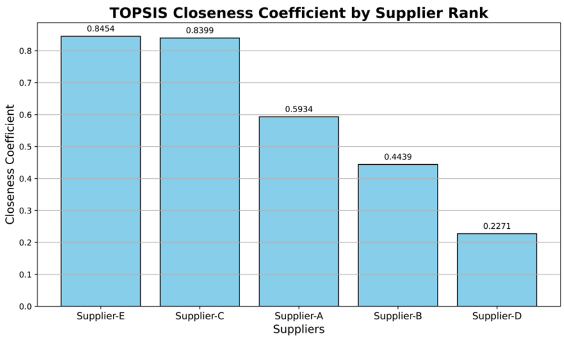

Fig. 7. Final supplier ranking using TOPSIS.

The sensitivity analysis involves examining how changes in criteria weights or performance ratings affect the final supplier ranking, which helps in assessing the stability and robustness of the decision-making outcome.

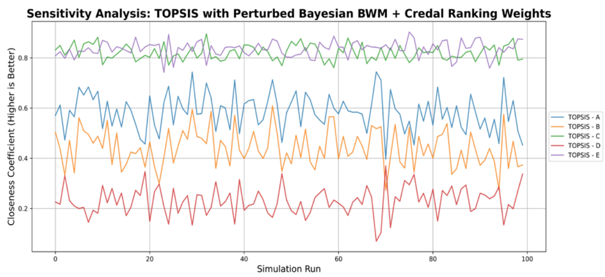

Fig. 8. Sensitivity analysis-TOPSIS.

The sensitivity analysis plot for the five suppliers (A–E) using hybrid TOPSIS approach is given in Fig. 8. It displays the sensitivity analysis based on closeness coefficient for each supplier across 100 simulation runs with varied criteria weights. According to the Y-axis, a higher coefficient indicates a better performance. In this case the supplier (C) and supplier (E) are consistently at the top of the chart, which indicates that they are robustly the best options. They frequently switch positions for the top rank, but they are always the top 2 choices, regardless of the changes in criteria weights. The suppliers are clearly separated into distinct performance groups.

V. CONCLUSION AND FUTURE WORK

The integration of Bayesian BWM and credal ranking into the Fuzzy VIKOR framework provides a robust and systematic approach for handling uncertainty and expert variability in multi-criteria supplier selection problems. Bayesian BWM effectively incorporates subjective judgments from multiple experts while managing inconsistencies in pairwise comparisons. The resulting probabilistic weights reflect both the relative importance of criteria and the confidence in those preferences, improving the credibility of the decision-making process.

The use of credal ranking probabilities further refines this by capturing epistemic uncertainty. The use of triangular fuzzy numbers helps to handle imprecision in the performance ratings of suppliers. Fuzzy VIKOR approach accommodates both qualitative and quantitative data, which allows for trade-offs between group utility (S) and individual regret (R), and identifies the most compromise-suitable supplier using the Q value. The probabilistic weights are applied to the decision matrix used by Fuzzy VIKOR and the Fuzzy TOPSIS method is been applied. The Fuzzy TOPSIS method calculates a closeness coefficient score, which tells how much a particular alternative is close to the best suitable supplier. When choosing a supplier, it is preferable to choose one with a higher closeness coefficient score.

The TOPSIS analysis strongly corroborates the results from the previous VIKOR analysis. Both methods independently identify Supplier C and Supplier E as the top performers and Suppliers D is the least preferred. This consistency across different evaluation methods provides a very high level of confidence in the final decision.

The final result is a comprehensive and resilient supplier ranking, which remains stable even under uncertainty, as demonstrated by sensitivity analysis. This ensures that the decision-maker is selecting a supplier not just based on the average opinion, but with full awareness of potential variability in both preferences and performance evaluations.

The final ranks in this MCDM-driven paradigm may be biased and subjective due to expert ratings and judgments. A possible approach that can be used in future works is to enhance or substitute expert assessments with data-driven evaluations of supplier performance, utilising previous operational records. Certain predictive models can be used to generate objective and continuously updated performance scores. These model-derived scores can then be integrated into a hybrid decision framework, where MCDM acts as a transparent aggregator of empirically estimated criteria rather than subjective ratings.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

IM conceptualized the research idea, designed the methodology, conducted the experimental analysis, and drafted the initial manuscript. BN contributed to system development and implementation, and assisted with manuscript revisions. Both authors discussed the results and approved the final manuscript for publication.

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