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An interval-valued fuzzy MULTIMOOSRAL method for supplier evaluation in oil production projects

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Abstract –Meticulous project planning is pivotal for ensuring successful project outcomes, with strategic decision-making being a core component of this process. Among these decisions, selecting the right contractor is of paramount importance, particularly in the oil and gas sector where complexity, stringent safety regulations, and significant financial stakes are prevalent. The choice of contractor can significantly affect the project's success, highlighting the need for a meticulous selection process. This study presents a new approach for supplier selection in the oil and gas industry, utilizing an Interval-Valued Fuzzy MULTIMOOSRAL (IVF-MULTIMOOSRAL) method. This advanced methodology synthesizes the strengths of MOOSRA, MOORA, and MULTIMOORA techniques with interval-valued fuzzy sets to manage uncertainties in decision-making. Through a case study involving the evaluation of ten potential suppliers for a Vietnamese petroleum company, the IVF-MULTIMOOSRAL method demonstrates its practical application. The study assesses suppliers based on fifteen sub-criteria within five main categories: reliability, capability, agility, effective asset management, and cost. By providing a comprehensive framework for evaluating suppliers amidst uncertainty, this method facilitates more informed and adequate decision-making in the oil and gas supply chain. The IVF-MULTIMOOSRAL approach distinguishes itself by evaluating and ranking options across multiple criteria, ultimately integrating these assessments into a unified rating. This multifaceted approach not only enhances the precision of the selection process but also underscores the critical nature of the factors being evaluated.

Keywords*–Supplier selection, Oil production projects, MCDM, Interval-Valued Fuzzy Sets, IVF-MULTIMOOSRAL.*

I. INTRODUCTION

The oil industry holds a critical position in the global economy, serving as a fundamental pillar across various sectors due to its widespread applications. Crude oil and its derivatives are indispensable resources that fuel industries such as pharmaceuticals, chemicals, electricity, agriculture, and many others. This central role cements the oil industry's status as a linchpin of international industrial success. The persistent rise in global crude oil demand further accentuates its importance. Daily consumption rose from 84.8 million barrels in 2010 to 102.21 million barrels in 2023, and it is expected to increase to 104.1 million barrels in 2024 (Gidiagba et al. 2023). This growing demand trajectory underscores the sustained and escalating dependence on oil, affirming its integral role in the global economic structure.

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The coordination of the distribution of oil and gas products from their origins to their endpoints has assumed a critical role in ensuring the effective and efficient delivery of these resources across the supply chain. As a result, the selection of suppliers has become a fundamental and strategic component of supply chain management (Sarkis and Talluri, 2002), demanding rigorous evaluation and strategic foresight. In the context of ongoing industrialization and modernization, it is imperative for businesses to meticulously assess this decision to optimize operational efficiency, mitigate risks, and sustain a competitive advantage in an increasingly complex global market.

The selection of appropriate suppliers is fundamentally linked to the utilization of Multi-Criteria Decision-Making (MCDM) approaches (Machesa et al. 2020), given the intricate and multifaceted nature of the evaluative factors involved. Assessing criteria such as cost, quality, reliability, delivery performance, and sustainability requires careful consideration, as each factor holds varying degrees of importance. This decision-making process demands the integration of both quantitative and qualitative information to navigate trade-offs and rank suppliers based on the organization's specific needs and strategic objectives. By employing MCDM methods, a thorough analysis and comparison of these factors can be achieved, leading to a more informed and balanced selection process that enhances operational efficiency and aligns with long-term strategic goals.

MCDM methods have been extensively utilized for supplier selection within the petroleum and natural gas industry, given their proven effectiveness in managing these decisions' intricate and multifaceted nature. Numerous studies have highlighted the efficiency of MCDM techniques in this sector. For instance, Wood (2016) emphasized the application of fuzzy and intuitionistic fuzzy TOPSIS, enhanced with flexible entropy weighting, for selecting suppliers in the development of petroleum industry facilities. Similarly, Gidiaba et al. (2023) investigated sustainable supplier selection through an integrated MCDM approach, underscoring the increasing importance of sustainability considerations in the industry.

Further exemplifying the robustness of MCDM methods, Wang et al. (2018) employed a hybrid approach that combines SCOR metrics, AHP, and TOPSIS for the evaluation and selection of suppliers in the gas and oil industry. Additionally, Wang et al. (2020) developed an MCDM model specifically tailored for supplier evaluation and selection in oil production projects in Vietnam, demonstrating the method's adaptability across different contexts. Nasri et al. (2023) introduced a sustainable supplier selection methodology utilizing an integrated Fuzzy DEMATEL–ANP–DEA approach, particularly within the petroleum industry, reinforcing the relevance and applicability of MCDM techniques in achieving both efficient and sustainable supplier selection outcomes.

Despite considerable advancements in supplier selection methodologies, significant gaps remain in effectively addressing the uncertainties inherent in the oil and gas industry. Traditional methods often fall short in capturing the nuanced, imprecise nature of decision-makers' judgments, which can lead to less optimal supplier choices. The complexity of the oil and gas sector—characterized by its high stakes, stringent safety requirements, and dynamic market conditions—demands a more sophisticated approach that can manage these uncertainties comprehensively. Existing techniques frequently lack the robustness needed to integrate diverse criteria and address the vagueness present in real-world decision-making processes, thereby highlighting the need for a more refined solution.

In the oil and gas industry, selecting the most suitable supplier is a complex process fraught with uncertainty due to the dynamic and multifaceted nature of the sector. To address this challenge, our research aims to develop a refined supplier selection approach that integrates new MULTIMOOSRAL methodology with Interval-Valued Fuzzy Sets (IVFSs). This innovative approach seeks to enhance the decision-making process by accommodating the inherent uncertainties and complexities associated with evaluating suppliers. By incorporating IVFSs, we can better capture the variability and imprecision in decision-makers' judgments, providing a more nuanced and flexible framework for supplier selection. This integrated method promises to improve both the accuracy and robustness of the decision-making process, ensuring that the selected suppliers align with the industry's rigorous requirements.

To validate the effectiveness of the proposed IVF-MULTIMOOSRAL approach, this study will address key research questions concerning its integration with IVFSs, the identification of relevant criteria and sub-criteria, and its performance compared to existing MCDM techniques. We will explore how the new method can be effectively applied in real-world scenarios, assessing its ability to handle uncertainties and improve decision outcomes. By comparing the proposed method with traditional MCDM techniques, we aim to demonstrate its superiority in terms of accuracy and flexibility, ultimately providing a robust framework that enhances the supplier selection process in the oil and gas sector.

The remainder of this article is organized as follows: Section 2 covers the literature review. Section 3 provides an overview of the definitions and operators of IVFSs. The new integrated MULTIMOOSRAL approach is detailed in Section 4. In Section 5, a corresponding numerical example is presented. The results and sensitivity analysis are examined in Section 6. Lastly, Section 7 concludes the article.

II. LITERATURE REVIEW

Over the past few decades, a variety of well-established MCDM methods have become essential tools for decision-makers tackling the challenge of evaluating numerous alternatives against multiple criteria using quantitative techniques. Among these, maxmax and maxmin methods are noted for their optimistic and pessimistic approaches, respectively. The SAW method calculates aggregate scores by weighting different criteria. The AHP and ANP employ hierarchical structures and pairwise comparisons for their evaluations. ELECTRE and PROMETHEE are outranking methods that determine priorities based on relative dominance among alternatives. TOPSIS and VIKOR focus on assessing alternatives based on their closeness to an ideal solution, whereas COPRAS employs a complex proportional assessment for evaluation. MACBETH, on the other hand, uses interval judgments to create a preference scale. Collectively, these methods provide comprehensive frameworks that significantly enhance the process of making informed decisions in multi-criteria scenarios (Ulutaş et al. 2020).

In recent years, the necessity to address a diverse array of real-world problems has driven the development of a new generation of MCDM methods. Notable among these are the HEBIN method introduced by (Zavadskas et al. 2021), and the MARCOS method developed by (Stević et al. 2020). The CoCoSo method, formulated by (Yazdani et al. 2019), and the SECA method by Keshavarz-Ghorabaee et al. in 2018 have also made significant contributions (Keshavarz-Ghorabaee et al. 2018). Additionally, the FUCOM method, introduced by (Pamučar et al. 2018), and the ARCAS method by (Stanujkic et al. 2017) have expanded the toolbox of MCDM techniques. The PIPRECIA method, also from (Stanujkić et al. 2017), the MABAC method by (Pamučar and Ćirović 2015), and the EDAS method from (Ghorabaee et al. 2015), further exemplify the innovative approaches being developed to enhance decision-making in complex scenarios.

The Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method, introduced by (Brauers, 2004), has proven to be a versatile and robust tool for various decision-making processes across different fields. Karande and Chakraborty (2012) highlighted its effectiveness in materials selection, where the correct choice of materials is critical for product performance and longevity. They demonstrated that MOORA, with its ability to remain unaffected by criteria weights and normalization procedures, offered a straightforward and accurate approach for ranking material alternatives, thus preventing premature product failures. Attri and Grover (2014) extended the application of MOORA to the complex decision-making environment of production systems. Their research underscored MOORA's capability to balance multiple conflicting criteria efficiently, making it a valuable tool for managing the diverse and subjective inputs required in production system life cycles (Attri and Grover, 2014).

Beyond these applications, MOORA has been effectively integrated with fuzzy logic and other decision-making methods to address specific needs in various sectors. Ozcelik et al. (2014) utilized a hybrid MOORA-fuzzy algorithm to select the best special education and rehabilitation center in Kayseri, Turkey, considering a range of criteria from education quality to cost and public opinion (Ozcelik et al. 2014). Similarly, Akkaya et al. (2015) applied a fuzzy AHP and MOORA approach to guide Industrial Engineering students in Turkey on their sector preferences, identifying technology, software/informatics, and finance as top choices. Siddiqui and Tyagi (2016) proposed a Fuzzy-MOORA method to rank software components based on reliability in component-based software systems, offering a non-subjective and precise ranking mechanism (Siddiqui and Tyagi, 2016). Additionally, Patnaik et al. (2020) combined AHP and MOORA to select composite materials for structural applications, focusing on properties like wear resistance (Patnaik et al. 2020), while Emovon et al. (2021) applied fuzzy MOORA to design an affordable automated hammering machine for developing countries (Emovon et al. 2021). Lastly, Khorshidi et al. (2022) integrated fuzzy DEMATEL and MOORA to determine optimal locations for solar power plants in Turkey, supporting renewable energy initiatives and addressing global warming. These diverse applications illustrate MOORA's adaptability and effectiveness in solving complex MCDM problems.

Based on the foundational ideas of the MOORA method, Brauers and Zavadskas (2010) proposed the Multi-Objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) method to enhance decision-making processes. This advancement addresses the complexity of dealing with multiple objectives expressed in different units by utilizing a ratio system to produce dimensionless numbers, thus avoiding the biases introduced by subjective weights. Brauers and Zavadskas (2011) demonstrated the practical application of MULTIMOORA in deciding on a bank loan for a property purchase.

The MULTIMOORA method has since been applied across various domains, proving its versatility and effectiveness. For instance, Baležentis et al. (2012) developed the MULTIMOORA-FG method for personnel selection, incorporating fuzzy logic to manage uncertainty and enhance group decision-making. Aytaç Adalı and Tuş Işık (2017) applied MULTIMOORA to laptop selection, showcasing its utility in consumer decision-making scenarios. In renewable energy, Alkan and Albayrak (2020) used fuzzy MULTIMOORA to rank energy sources for different regions in Turkey, while Liu et al. (2021) extended MULTIMOORA for sustainable supplier selection, introducing Intuitionistic Linguistic Rough Numbers (ILRNs) to better capture expert opinions (Liu et al. 2021). The method's adaptability is further illustrated by its application in food waste treatment selection (Rani et al., 2021), supplier selection in sustainable supply chains (Shang et al., 2022), CO2 geological storage site selection (Yang & Zhang, 2023), and assessing sustainable third-party reverse logistics providers (Rong et al., 2024). These studies highlight MULTIMOORA's capability to handle diverse, complex decision-making problems effectively.

Ulutaş et al. (2021) developed the MULTIMOOSRAL approach, a new MCDM method designed to enhance the selection process for alternatives. This approach combines the strengths of three prominent MCDM methods: MOOSRA, MOORA, and MULTIMOORA, while integrating elements from the WASPAS and CoCoSo methods, which utilize weighted sum and weighted product approaches. Additionally, the MULTIMOOSRAL method incorporates a logarithmic approximation approach, offering a more reliable and nuanced selection process, especially in scenarios where alternative performances are closely matched. The new method replaces the dominance theory used in MOORA and MULTIMOORA with an original approach for simpler and stronger final rankings. The efficacy of MULTIMOOSRAL was demonstrated through a case study on supplier selection, showcasing its practical applicability and reliability.

Shayani Mehr et al. (2022) utilized the BWM-MULTIMOOSRAL framework for selecting solar panel technologies, considering nine technologies across five sustainable criteria. Their analysis identified CIS/CIGS and Perovskite Solar cells as the top choices for specific locations. Biswas et al. (2022) extended the MULTIMOOSRAL method with spherical fuzzy numbers to evaluate the leanness of MSMEs in India. They incorporated expert opinions to assess criteria such as leadership, process management, and customer focus, finding that leadership commitment and waste reduction are crucial for achieving leanness. The study's results were validated through sensitivity analysis and comparison with the TOPSIS method, demonstrating the accuracy and stability of the SF-LBWA-MULTIMOOSRAL framework. These applications underscore the method's effectiveness in diverse decision-making scenarios, from renewable energy to manufacturing efficiency.

Recent advancements in MCDM have focused on developing innovative frameworks to tackle complex environmental and energy-related challenges. Wang et al. (2024) introduced a new approach for assessing ecological governance in the Yellow River basin, a region of strategic importance in China. Their methodology combines the Best-Worst Method (BWM) using linguistic variables for subjective weight assignment with an Improved Grey Relational (IGR) method for objective weight calculation. These weights are integrated through the Uninorm operator to ensure a balanced evaluation of indicators. They refined the assessment by developing the MULTIMOORA-Borda method, which synthesizes multiple evaluations from MULTIMOORA to offer comprehensive policy insights. This study illustrated the adaptability of MCDM methods in environmental governance contexts. Similarly, Zhou et al. (2024) developed a decision-making framework for offshore wind power station site selection using an extended MULTIMOORA method under a Pythagorean hesitant fuzzy environment. The framework establishes an evaluation attribute system, applies Pythagorean hesitant fuzzy sets to capture evaluation information, uses an improved SWARA method for attribute weighting, and ranks alternatives with an extended MULTIMOORA approach.

In the area of Multi-Attribute Group Decision-Making (MAGDM), cognitive computational techniques and advanced algorithms have been pivotal in addressing complex decision-making problems. Bai et al. (2024) explored the stability of the MULTIMOORA method combined with evidential reasoning (ER) to manage MAGDM challenges effectively. They introduced multiorganization probabilistic rough sets (MG PRSs) and employed hierarchical clustering to aggregate decision information, streamline the process, and reduce complexity by decreasing the model's dimensionality. The proposed approach was validated using a case study on chickenpox data from the UCI dataset, highlighting the method's effectiveness in enhancing decision stability and reducing uncertainty.

Concurrently, Rong et al. (2024) developed a framework for selecting sustainable third-party reverse logistics providers (S3PRLPs) amid uncertain and conflicting data. They utilized q-rung orthopair fuzzy (q-ROF) sets combined with the Best-Worst Method (BWM), MULTIMOORA, and Weighted Aggregated Sum Product Assessment (WASPAS). This approach, which incorporates new scoring and interactive operators, was validated through empirical testing, proving effective in improving logistics decision-making and service quality. These developments highlight the expanding use of MCDM methods in addressing complex real-world problems. Table 1 provides a concise overview of the studies that utilize the MOORA, MULTIMOORA, and MULTIMOOSRAL methods, highlighting the uncertainty addressed in each study.

Table 1. Overview of Studies Utilizing MOORA, MULTIMOORA, and MULTIMOOSRAL Methods

Num.	Auther(s)	Year	Method			Uncertainty	
			MOORA	MULTIMOORA	MULTIMOOSRAL	Fuzzy Set	Interval-Valued fuzzy set
1	Brauers & Zavadskas	2006	*				
2	Brauers & Zavadskas	2010		*			
3	Brauers & Zavadskas	2011		*			
4	Karande & Chakraborty	2012	*				
5	Baležentis et al.	2012		*		*	
6	Attri & Grover	2014	*				
7	Ozcelik et al.	2014	*			*	
8	Akkaya et al.	2015	*				
9	Siddiqui & Tyagi	2016	*			*	
10	Aytaç Adalı & Tuş Işık	2017		*			
11	Patnaik et al.	2020	*				
12	Alkan & Albayrak	2020		*		*	

Continue Table 2. Overview of Studies Utilizing MOORA, MULTIMOORA, and MULTIMOOSRAL Methods

Num.	Auther(s)	Year	Method			Uncertainty	
			MOORA	MULTIMOORA	MULTIMOOSRAL	Fuzzy Set	Interval-Valued fuzzy set
13	Ulutaş et al.	2021			*		
14	Emovon et al.	2021	*				
15	Liu et al.	2021		*			
16	Rani et al.	2021		*			
17	Khorshidi et al.	2022	*			*	
18	Shang et al.	2022		*		*	
19	Shayani Mehr et al.	2022			*		
20	Biswas et al.	2022			*		
21	Yang & Zhang	2023		*		*	
22	Rong et al.	2024		*		*	
23	Wang et al.	2024		*			
24	Zhou & Geng	2024		*		*	
25	Bai et al.	2024		*			
26	Rong et al.	2024		*		*	
This study			*		*		*

Despite the growing interest in advanced MCDM methods, only a few studies have utilized the newly developed MULTIMOOSRAL approach. This novel method, which integrates the strengths of MOOSRA, MOORA, and MULTIMOORA, has shown promise in improving the reliability and robustness of alternative selection. However, its application remains limited, leaving a significant gap in the literature. Furthermore, while IVFSs represent a significant advancement in the field of fuzzy set theory, their potential has not yet been fully explored within the context of MULTIMOOSRAL. The incorporation of IVFSs could enhance the ability of MULTIMOOSRAL to handle uncertainty and imprecision more effectively.

This study aims to bridge the existing gap in supplier selection methodologies specific to the oil and gas industry by merging the MULTIMOOSRAL method with IVFSs. Although the MULTIMOOSRAL method has demonstrated promise in refining decision-making processes, its application in the context of oil and gas supplier selection remains underexplored. By integrating IVFSs, which are recognized for their sophisticated management of uncertainty and imprecision, this research intends to significantly improve the precision of supplier assessments. The goal is to create a more thorough and dependable decision-making framework that addresses the unique complexities and multi-criteria challenges inherent in supplier selection within the oil and gas sector.

III. INTERVAL-VALUED FUZZY SETS

Linguistic values present a distinct benefit for managing intricate and vague situations that are difficult to quantify or measure precisely. These values, expressed through linguistic terms, simplify the expression of subjective and qualitative uncertainties commonly encountered in decision-making. According to Zadeh and Zimmermann, a linguistic variable is characterized by values **expressed** in linguistic terms, offering a more detailed and nuanced perspective on the scenario being assessed (Zadeh, 1975; Zimmerman, 1986).

Traditional fuzzy sets often fall short in effectively capturing the subtleties of linguistic expressions. The work of Grattan in the 1970s, and later the contributions by Karnik and Mendel in 2001, demonstrated that IVFSs offer enhanced flexibility for representing uncertain or vague information (Grattan-Guinness, 1976; Karnik and Mendel, 2001). Unlike traditional fuzzy sets, IVFSs accommodate a wider range of possible values, thereby providing decision-makers with greater latitude in articulating their evaluations and judgments. This flexibility is particularly beneficial in capturing the nuances of linguistic expressions, leading to a clearer and more accurate representation of imprecise data. The significance of IVFSs is further supported by Ashtiani et al. (2009) and Vahdani et al. (2010), who argue that these sets are instrumental in managing complex and ambiguous decision-making scenarios. By offering a more refined approach to handling uncertainty, IVFSs enable decision-makers to navigate intricate problems with improved accuracy and effectiveness (Ashtiani et al., 2009; Vahdani et al., 2010).

This study explores the notion of fuzzy demand through the lens of IVFSs. It builds on Gorzalczany's (Gorzałczany, 1987), definition of $\widetilde{X}$, an IVFS that spans the entire range from $-\infty$ to $+\infty$.

$$\widetilde{X} = \{x, [\mu_{\widetilde{X}^l}(x), \mu_{\widetilde{X}^u}(x)]\}, \qquad x \in (-\infty, \infty), \qquad \mu_{\widetilde{X}^l}, \mu_{\widetilde{X}^u} : (-\infty, \infty) \to [0, 1],$$

$$\mu_{\widetilde{X}}(x) = [\mu_{\widetilde{X}^l}(x), \mu_{\widetilde{X}^u}(x)], \qquad \mu_{\widetilde{X}^l}(x) \le \mu_{\widetilde{X}^u}(x), \qquad \forall x \in (-\infty, \infty),$$

where $\mu_{\widetilde{X}^l}(x)$ and $\mu_{\widetilde{X}^u}(x)$ represent the minimum and maximum limits of the degree of membership.

Additionally, according to (Yao and Lin, 2002) characterization of triangular interval-valued fuzzy numbers (IVFNs), which is illustrated in Figure 1, a triangular IVFN can be represented as $\widetilde{X} = [\widetilde{X}^l, \widetilde{X}^u] = [(x^2, {x_l}^3, x^4; \hat{y}^l_{\widetilde{X}}), (x^1, {x_u}^3, x^5; \hat{y}^u_{\widetilde{X}})]$. Where $\widetilde{X}^l$ and $\widetilde{X}^u$ are used to denote the lower and upper triangular IVFNs. The membership function $\mu_{\widetilde{X}}(x)$ quantifies how strongly an element x belongs to the fuzzy set $\widetilde{X}$; Specifically, $\mu_{\widetilde{X}^l}(x) = \hat{y}^l_{\widetilde{X}}$ and $\mu_{\widetilde{X}^u}(x) = \hat{y}^u_{\widetilde{X}}$ represent the membership values for the lower and upper bounds of the fuzzy set, respectively. Based on Figure 1, the following relationships can be derived:

1. When $\tilde{X}^l$ and $\tilde{X}^u$ are identical, the triangular IVFN $\tilde{X}$ effectively represents a generalized triangular fuzzy number.
2. If the lower and upper limits of all parameters and membership values are identical, then the triangular IVFN $\tilde{X}$ represents a crisp value.
3. If the lower and upper membership values for $\tilde{X}$ are both 1, and ${x_l}^3 = {x_u}^3$, then the triangular IVFN $\tilde{X}$ can be represented as $\tilde{X} = [(x^1, x^2); x^3; (x^4, x^5)]$

According to the third relationship outlined above, two triangular IVFNs can be expressed as $\tilde{X}_1 = [(x_1^1, x_1^2); x_1^3; (x_1^4, x_1^5)]$ and $\tilde{X}_2 = [(x_2^1, x_2^2); x_2^3; (x_2^4, x_2^5)]$, Following this, the studies by (Chen, 1997; Hong and Lee, 2002; Chen and Chen, 2008; Vahdani et al. 2010), introduced operations including addition, subtraction, multiplication, generalized division, and n-dimensional between $\tilde{X}_1$ and $\tilde{X}_2$, which are outlined below:

1. Addition of IVFNs $\oplus$:

$$\tilde{X}_1 \oplus \tilde{X}_2 = [(x_1^1 + x_1^1, x_1^2 + x_2^2); x_1^3 + x_2^3; (x_1^4 + x_2^4, x_1^5 + x_2^5)] \tag{1}$$

2. Subtraction of IVFNs $\ominus$:

$$\tilde{X}_1 \ominus \tilde{X}_2 = [(x_1^1 - x_1^5, x_1^2 - x_2^4); x_1^3 - x_2^3; (x_1^4 - x_2^2, x_1^5 - x_2^1)] \tag{2}$$

3. Multiplication of IVFNs $\otimes$:

$$\tilde{X}_1 \otimes \tilde{X}_2 = [(x_1^1 \times x_1^1, x_1^2 \times x_2^2); x_1^3 \times x_2^3; (x_1^4 \times x_2^4, x_1^5 \times x_2^5)] \tag{3}$$

4. Generalized division of IVFNs $\oslash$:

$$\frac{\tilde{X}_1}{\tilde{X}_2} = [\left(\frac{x_1^1}{x_2^5}, \frac{x_1^2}{x_2^4}\right); \frac{x_1^3}{x_2^3}; (\frac{x_1^4}{x_2^2}, \frac{x_1^5}{x_2^1})] \tag{4}$$

5. Scalar multiplication of the IVFN by k:

$$k\tilde{X}_1 = [(kx_1^1, kx_1^2); kx_1^3; (kx_1^4, kx_1^5)] \tag{5}$$

6. Inverse of IVFN:

$$\frac{1}{\tilde{X}_1} = [\left(\frac{1}{x_1^5}, \frac{1}{x_1^4}\right); \frac{1}{x_1^3}; (\frac{1}{x_1^2}, \frac{1}{x_1^1})] \tag{6}$$

7. n-dimensional of IVFN:

$$\tilde{X}_1{}^n = [\left(x_1^{1\,n}, x_1^{1\,n}\right); x_1^{3\,n}; (x_1^{4\,n}, x_1^{5\,n})] \tag{7}$$

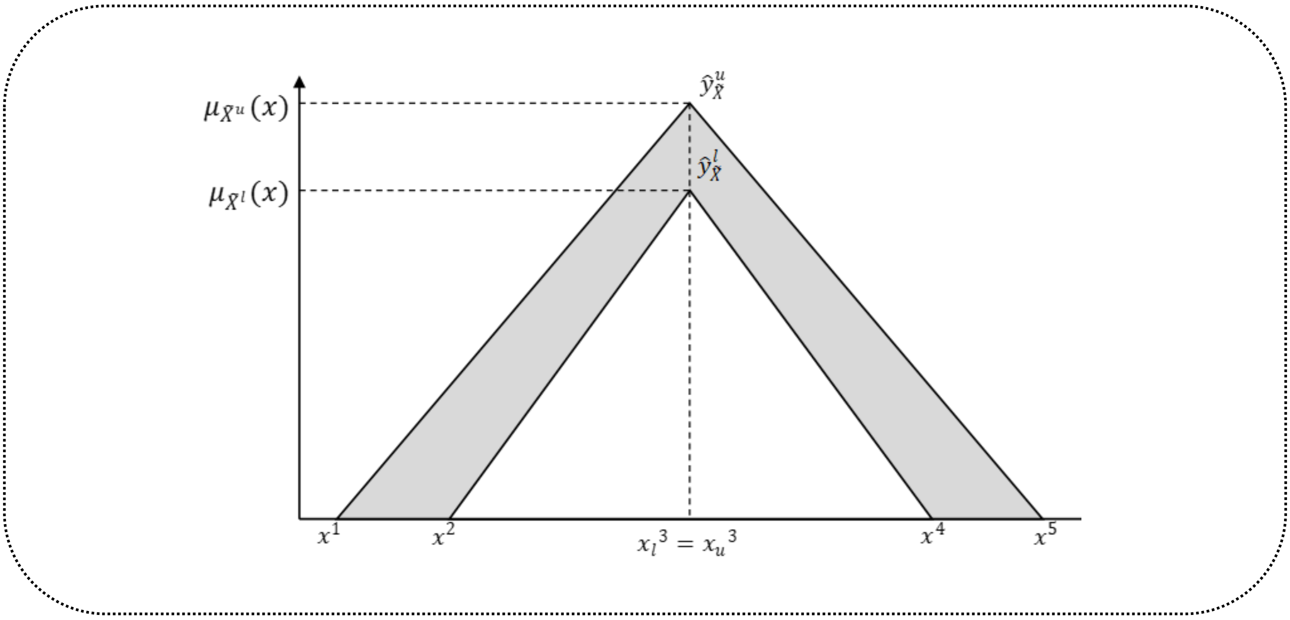

Fig. 1. An interval-valued triangular fuzzy number

IV. PROPOSED METHODOLOGY

The integrated approach IVF-MULTIMOOSRAL leverages the framework of the newly proposed MULTIMOOSRAL method, designed for MCDM. This method synthesizes elements from MOOSRA, MOORA, and MULTIMOORA, enhanced by the logarithmic approximation (LA) approach, to improve the decision-making process (Figure 2). The core idea behind MULTIMOOSRAL is to increase the credibility and reliability of the obtained results by integrating five distinct ranking approaches: the Ratio System (RS), Reference Point (RP), Full Multiplicative Form (FMF), Addition Form (AF), and Logarithmic Approximation (LA) (Figure 3). By combining these methods, MULTIMOOSRAL addresses various aspects of decision criteria, leading to a more stable and reliable ranking of alternatives.

Incorporating IVFSs into MULTIMOOSRAL, the IVF-MULTIMOOSRAL approach further enhances the decision-making framework by accounting for uncertainty and imprecision inherent in real-world scenarios. IVFSs allow for the representation of data with a range of values rather than precise single points, thus providing a more flexible and comprehensive evaluation of alternatives. This integration ensures that the MULTIMOOSRAL method can handle vague and ambiguous information effectively, leading to more nuanced and accurate decision-making outcomes. The combination of IVFSs with the multifaceted ranking system of MULTIMOOSRAL ensures that the final ranking order of alternatives is both credible and robust, accommodating the complexities and uncertainties typical in many decision-making environments.

The following outlines the procedural steps for the integrated IVF-MULTIMOOSRAL method:

Step 1: Formulating the initial decision matrix and determining criteria weights:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & & \tilde{x}_{2n} \\ \vdots & & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}, \qquad i = 1, 2, \ldots, m, \qquad j = 1, 2, \ldots, n. \tag{8}$$

Where $\tilde{x}_{ij}$ is IVFN and can be represented as $\tilde{x}_{ij} = \left[\left(x_{ij}^1, x_{ij}^2\right); x_{ij}^3; \left(x_{ij}^4, x_{ij}^5\right)\right]$.

Step 2: Constructing the normalized decision matrix:

$$\tilde{R} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \cdots & \tilde{r}_{1n} \\ \tilde{r}_{21} & \tilde{r}_{22} & & \tilde{r}_{2n} \\ \vdots & & \ddots & \vdots \\ \tilde{r}_{m1} & \tilde{r}_{m2} & \cdots & \tilde{r}_{mn} \end{bmatrix}, \tag{9}$$

Where $\tilde{r}_{ij}$ is IVFN and can be represented as $\tilde{r}_{ij} = \left[\left(r_{ij}^1, r_{ij}^2\right); r_{ij}^3; \left(r_{ij}^4, r_{ij}^5\right)\right]$, and

$$r_{ij}^1 = \frac{x_{ij}^1}{\sqrt{\sum_{i=1}^m \left[x_{ij}^1 + x_{ij}^2 + x_{ij}^3 + x_{ij}^4 + x_{ij}^5\right]}}, r_{ij}^2 = \frac{x_{ij}^2}{\sqrt{\sum_{i=1}^m \left[x_{ij}^1 + x_{ij}^2 + x_{ij}^3 + x_{ij}^4 + x_{ij}^5\right]}}, r_{ij}^3 = \frac{x_{ij}^3}{\sqrt{\sum_{i=1}^m \left[x_{ij}^1 + x_{ij}^2 + x_{ij}^3 + x_{ij}^4 + x_{ij}^5\right]}}, r_{ij}^4 =$$

$$\frac{x_{ij}^4}{\sqrt{\sum_{i=1}^m \left[x_{ij}^1 + x_{ij}^2 + x_{ij}^3 + x_{ij}^4 + x_{ij}^5\right]}}, r_{ij}^5 = \frac{x_{ij}^5}{\sqrt{\sum_{i=1}^m \left[x_{ij}^1 + x_{ij}^2 + x_{ij}^3 + x_{ij}^4 + x_{ij}^5\right]}}.$$

Step 3: Calculating the Normalized Overall Utilities of Alternatives:

Utilize the five distinct approaches embedded within the MULTIMOOSRAL method—Ratio System (RS), Reference Point (RP), Full Multiplicative Form (FMF), Addition Form (AF), and Logarithmic Approximation (LA)—to determine the normalized overall utilities of the alternatives. This comprehensive calculation provides a robust assessment of each alternative, integrating the strengths of multiple methodologies.

Step 3.1: Evaluating the utility of alternatives using the RS approach through the following sub steps:

Sub step 3.1.1. Calculate the overall importance of alternatives: Perform this calculation as follows:

$$\tilde{y}_i = \sum_{j \in max} \tilde{p}_{ij} - \sum_{j \in min} \tilde{p}_{ij} \tag{10}$$

Where $\tilde{y}_i$ is IVFN and can be represented as $\tilde{y}_i = [(y_i^1, y_i^2); y_i^3; (y_i^4, y_i^5)]$, $\tilde{p}_{ij}$ is IVFN and can be represented as $\tilde{p}_{ij} = [(p_{ij}^1, p_{ij}^2); p_{ij}^3; (p_{ij}^4, p_{ij}^5)]$, $p_{ij}^1 = w_j^1 r_{ij}^1$, $p_{ij}^2 = w_j^2 r_{ij}^2$, $p_{ij}^3 = w_j^3 r_{ij}^3$, $p_{ij}^4 = w_j^4 r_{ij}^4$, $p_{ij}^5 = w_j^5 r_{ij}^5$ and $\widetilde{w}_j = [(w_j^1, w_j^2); w_j^3; (w_j^4, w_j^5)]$ is the relative IVF weights of each criterion. Then, the overall importance of considered alternatives is:

$$y_i = \frac{y_i^1 + y_i^2 + y_i^3 + y_i^4 + y_i^5}{5} \tag{11}$$

Sub step 3.1.2. Calculate the overall utility of alternatives: Determine the overall utility for each alternative, denoted as m_i, based on the RS approach.

$$m_i = f(x) = \begin{cases} y_i, & \max y_i > 0 \\ y_i + 1, & \max y_i = 0 \\ -\dfrac{1}{y_i}, & \max y_i < 0 \end{cases} \tag{12}$$

Sub step 3.1.3. Normalize the overall utilities: Normalize the utilities obtained from the RS approach, resulting in m_i', which represents the normalized overall utility of each alternative.

$$m'_i = \frac{m_i - \min m_i}{\max m_i - \min m_i} \tag{13}$$

Step 3.2. Evaluating the utility of alternatives using the RP approach through the following sub steps:

Sub step 3.2.1. Determine the Reference Point (RP) $\tilde{r}_j^* = [(r_j^{1*}, r_j^{2*}); r_j^{3*}; (r_j^{4*}, r_j^{5*})]$:

$$r_j^{1*} = \left\{ \max_i r_{ij}^1 \mid j \in max, \min_i r_{ij}^1 \mid j \in min \right\}, \tag{14}$$

$$r_j^{2*} = \left\{ \max_i r_{ij}^2 \mid j \in max, \min_i r_{ij}^2 \mid j \in min \right\}, \tag{15}$$

$$r_j^{3*} = \left\{ \max_i r_{ij}^3 \mid j \in max, \min_i r_{ij}^3 \mid j \in min \right\}, \tag{16}$$

$$r_j^{4*} = \left\{ \max_i r_{ij}^4 \mid j \in max, \min_i r_{ij}^4 \mid j \in min \right\}, \tag{17}$$

$$r_j^{5*} = \left\{ \max_i r_{ij}^5 \mid j \in max, \min_i r_{ij}^5 \mid j \in min \right\}. \tag{18}$$

Sub step 3.2.2. Calculate the maximal distance: the maximal distance t_i is calculated by first determining the absolute differences between each alternative and the reference point, weighting these differences, and then averaging the weighted differences. The absolute differences between each alternative and the Reference Point (RP) $\tilde{q}_{ij}$ is IVFN and can be represented as $\tilde{q}_{ij} = [(q_{ij}^1, q_{ij}^2); q_{ij}^3; (q_{ij}^4, q_{ij}^5)]$, $q_{ij}^1 = |r_j^{1*} - r_{ij}^5|$, $q_{ij}^2 = |r_j^{2*} - r_{ij}^4|$, $q_{ij}^3 = |r_j^{3*} - r_{ij}^3|$, $q_{ij}^4 = |r_j^{4*} - r_{ij}^2|$, and $q_{ij}^5 = |r_j^{5*} - r_{ij}^1|$.

Consequently, multiply the absolute differences by the corresponding weights. The weighted differences, denoted as $\tilde{t}_i$, can be expressed as $\tilde{t}_i = \left[(t_i^1, t_i^2); t_i^3; (t_i^4, t_i^5)\right]$, where $t_i^1 = w_j^1 q_{ij}^1$, $t_i^2 = w_j^2 q_{ij}^2$, $t_i^3 = w_j^3 q_{ij}^3$, $t_i^4 = w_j^4 q_{ij}^4$, and $t_i^5 = w_j^5 q_{ij}^5$.

Finally, Compute the maximal distance t_i using Equation (19):

$$t_i = \frac{t_i^1 + t_i^2 + t_i^3 + t_i^4 + t_i^5}{5} \tag{19}$$

Sub step 3.2.3. Normalize the maximal distances: Use Equation (20) to normalize the distances, resulting in t'_i, which represents the normalized overall utility of each alternative based on the RP approach.

$$t'_i = \frac{t_i - \min t_i}{\max t_i - \min t_i} \tag{20}$$

Step 3.3: Evaluating the utility of alternatives using the FMF Approach, follow these sub steps to evaluate the utility of the alternatives:

Sub step 3.3.1: Compute the Overall Utility of the Alternatives: Apply Equation (21) to determine the overall utility of each alternative:

$$u_i = \frac{\prod_{j \in max} p_{ij}}{\prod_{j \in min} p_{ij}} \tag{21}$$

Where $p_{ij} = \frac{p_{ij}^1 + p_{ij}^2 + p_{ij}^3 + p_{ij}^4 + p_{ij}^5}{5}$.

Sub step 3.3.2: Normalizing Overall Utilities: Normalize the calculated utilities using Equation (22):

$$u'_i = \frac{u_i - \min u_i}{\max u_i - \min u_i} \tag{22}$$

Here, u'_i represents the normalized overall utility of alternative i based on the FMF approach.

Step 3.4: Evaluating the utility of alternatives using the AF Approach

Substep 3.4.1: Calculating Overall Utility

To determine the overall utility of each alternative using the AF approach, apply Equation (23):

$$v_i = \frac{\sum_{j \in max} p_{ij}}{\sum_{j \in min} p_{ij}} \tag{23}$$

Substep 3.4.2: Normalizing overall utilities

Normalize the calculated utilities using the following formula:

$$v'_i = \frac{v_i - \min v_i}{\max v_i - \min v_i} \tag{24}$$

Where v'_i represents the normalized overall utility of alternative i based on the AF approach.

Step 3.5: Evaluating the utility of alternatives using the LA Approach

Sub step 3.5.1: Calculating overall utility

To calculate the overall utility of each alternative based on the LA approach, use the following formula:

$$k_i = \sum_{j \in max} d_j + \frac{1}{\sum_{j \in min} d_j} \tag{25}$$

Here, $d_j = \frac{d_{ij}^1 + d_{ij}^2 + d_{ij}^3 + d_{ij}^4 + d_{ij}^5}{5}$, where $\tilde{d}_{ij}$ is IVFN represented as $\tilde{d}_{ij} = \left[\left(d_{ij}^1, d_{ij}^2\right); d_{ij}^3; \left(d_{ij}^4, d_{ij}^5\right)\right]$. The individual components are calculated as:

$$d_{ij}^1 = \ln\left(1 + p_{ij}^1\right), \tag{26}$$

$$d_{ij}^2 = \ln\left(1 + p_{ij}^2\right), \tag{27}$$

$$d_{ij}^3 = \ln\left(1 + p_{ij}^3\right), \tag{28}$$

$$d_{ij}^4 = \ln\left(1 + p_{ij}^4\right), \tag{29}$$

$$d_{ij}^5 = \ln\left(1 + p_{ij}^5\right). \tag{30}$$

Sub step 3.5.2: Normalizing overall utilities

Normalize the calculated utilities using the following formula:

$$k'_i = \frac{k_i - \min k_i}{\max k_i - \min k_i} \tag{31}$$

Here, k'_i denotes the normalized overall utility of alternative i based on the LA approach.

Step 4: Determining the Final Ranking Orders of Alternatives

The final ranking of alternatives is determined based on their total utility s_i, which is calculated as follows:

$$s_i = m'_i + t'_i + u'_i + v'_i + k'_i \tag{32}$$

Here, s_i represents the total utility of alternative iii, and it is the sum of the normalized utilities obtained from normalized utility from RS, RP, FMF, and LA approaches. The alternatives are ranked in descending order based on their s_i values. The alternative with the highest s_i value is considered the most preferable.

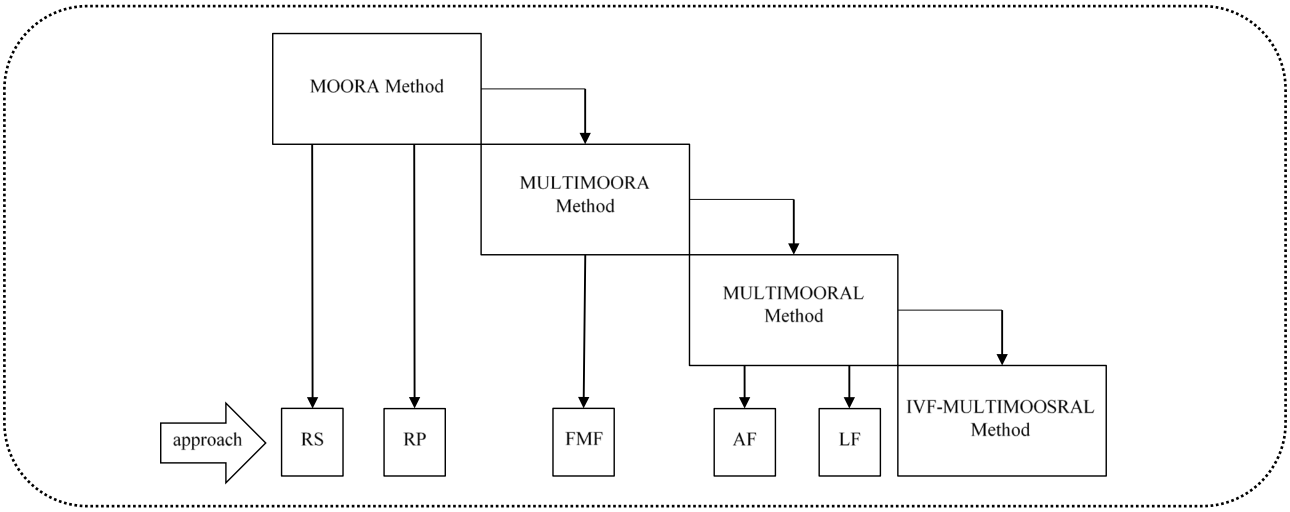

FIG. 2 . MULTIMOOSRAL METHOD

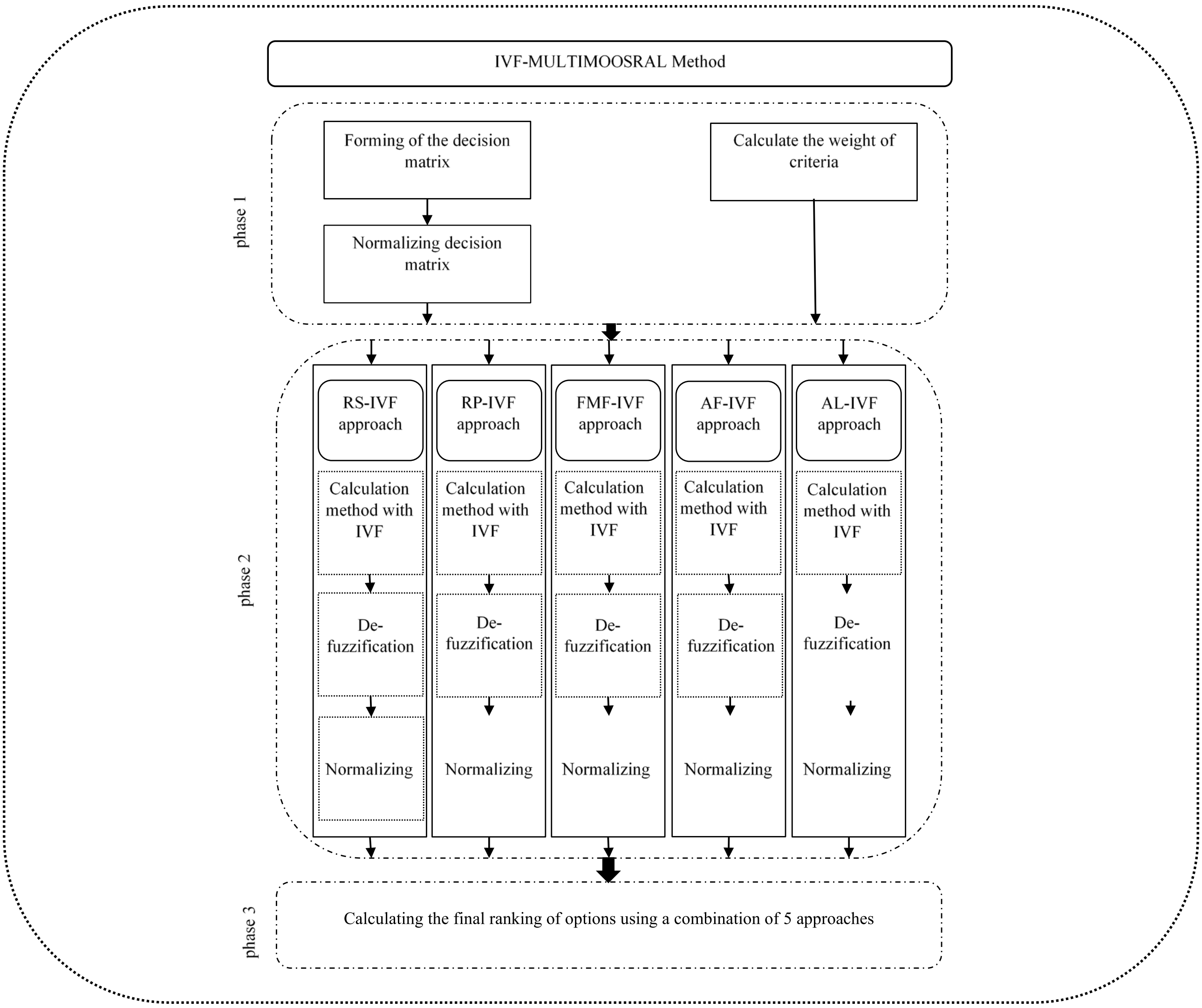

FIG. 3 .PROPOSED IVF-MULTIMOOSRAL METHOD

V. APPLICATIONN EXAMPLE

In this study, we draw on a case study from Wang et al. (2020), where the authors validated their model through a survey of suppliers at ABC Petroleum Joint Stock Company, a major oil and gas firm in Vietnam. The company's growth strategy includes expanding investments and optimizing its supply chain to meet increasing oil and gas demands. Wang et al. (2020) focused on assessing potential suppliers based on expert evaluations—particularly from the head of the purchasing department—and criteria such as raw material availability, pricing, and order fulfillment capabilities. Through this approach, they identified 10 suppliers that demonstrated high efficiency in meeting business needs. The potential suppliers identified in the study are detailed in Table 2.

The main and sub-criteria for selecting oil and gas suppliers, derived from the literature review, are presented in Table 3. The IVFNs corresponding to the linguistic variables are detailed in Table 4. Moreover, Tables 5 and 6 provide detailed insights into the evaluation process. Table 5 illustrates the relative importance of each sub-criterion, while Table 6 showcases the performance ratings of each supplier across these sub-criteria. These evaluations were conducted using linguistic variables, as determined by the decision-makers, to ensure a nuanced and comprehensive assessment. Finally, the integrated IVF-MULTIMOOSRAL methodology was employed to evaluate and rank the performance of each supplier. Through this comprehensive process, the final scores and rankings for each supplier were determined and are presented in Table 7, providing a clear overview of their respective standings.

Table 3 List of Suppliers and Corresponding Symbols

NO.	Suppliers Oil Production	Symbol
1	Supplier-01	DMU-01
2	Supplier-02	DMU-02
3	Supplier-03	DMU-03
4	Supplier-04	DMU-04
5	Supplier-05	DMU-05
6	Supplier-06	DMU-06
7	Supplier-07	DMU-07
8	Supplier-08	DMU-08
9	Supplier-09	DMU-09
10	Supplier-10	DMU-10

Table 4 Classification of Criteria and Sub criteria for Supplier Evaluation

Criteria		Subcriteria	
Symbol	**Main Criteria**	**Symbol**	**Main Subcriteria**
C_1	Reliability	C_{11}	Maximize delivery time
		C_{12}	Maximize the amount of delivery
		C_{13}	Maximize perfect conditions
		C_{14}	Maximize document accuracy
		C_{15}	Maximize compatibility
C_2	Ability	C_{21}	Minimize order fulfillment cycle time
		C_{22}	Minimize supplier’s need for corrective action, resolution time

Continue Table 5. Classification of Criteria and Sub criteria for Supplier Evaluation

Criteria		Subcriteria	
Symbol	**Main Criteria**	**Symbol**	**Main Criteria**
C_3	Agile	C_{31}	Maximize adaptability
		C_{32}	Maximize the downside adaptability
		C_{33}	Maximize flexibility
C_4	Effective asset management	C_{41}	Minimize cash to cash cycle time
		C_{42}	Minimize profits on fixed assets of the supply chain
C_5	Costs	C_{51}	Minimize Materials cost
		C_{52}	Minimize Shipping costs
		C_{53}	Minimize management costs

Table 6. IVFNs corresponding to linguistic variables

Linguistic variables	Symbol	Triangular interval-valued fuzzy numbers
Very low	VL	$[(0,0); 0 ; (0.1,0.15)]$
Low	L	$[(0,0.05); 0.1 ; (0.25,0.35)]$
Medium low	ML	$[(0,0.15); 0.3 ; (0.45,0.55)]$
Medium	M	$[(0.25,0.35); 0.5 ; (0.65,0.75)]$
Medium high	MH	$[(0.45,0.55); 0.7 ; (0.8,0.95)]$
High	H	$[(0.55,0.75); 0.9 ; (0.95,1)]$
Very high	VH	$[(0.85,0.95); 1 ; (1,1)]$

Table 7. Weights Assigned to Criteria and Subcriteria

Symbol Criteria	Symbol Subcriteria	Weight Criteria
C_1	C_{11}	VH
	C_{12}	MH
	C_{13}	M
	C_{14}	L
	C_{15}	H
C_2	C_{21}	M
	C_{22}	ML
C_3	C_{31}	MH
	C_{32}	M
	C_{33}	ML
C_4	C_{41}	H
	C_{42}	MH
C_5	C_{51}	MH
	C_{52}	M
	C_{53}	ML

Table 8 Linguistic Evaluation of Suppliers Across Multiple Criteria

Symbol Suppliers	C_1					C_2		C_3			C_4		C_5		
	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{51}	C_{52}	C_{53}
DMU-01	H	M	ML	M	VH	VH	MH	H	VH	L	H	VH	MH	MH	VH
DMU-02	ML	ML	MH	M	MH	M	H	MH	L	H	MH	VL	ML	H	L
DMU-03	M	MH	M	H	VH	H	MH	VH	MH	M	VH	MH	H	L	MH
DMU-04	L	M	H	MH	MH	L	ML	L	MH	MH	L	M	MH	M	H
DMU-05	VH	M	MH	L	VL	MH	M	H	VL	ML	MH	H	MH	ML	VL
DMU-06	VH	MH	VH	MH	H	ML	H	ML	H	MH	H	ML	VH	MH	M
DMU-07	VL	ML	L	L	M	H	L	MH	M	VH	M	MH	L	M	H
DMU-08	L	VH	H	M	MH	MH	VH	H	VL	MH	ML	VL	H	VH	MH
DMU-09	ML	VL	MH	ML	H	ML	MH	M	ML	MH	VL	MH	ML	MH	ML
DMU-10	M	MH	ML	MH	MH	M	H	ML	VL	ML	MH	MH	MH	H	VH

Table 9 Final Ranking and Scores of Oil Suppliers

NO.	Suppliers Oil Production	Symbol	The final amount	Rank
1	Supplier-01	DMU-01	1.628	8
2	Supplier-02	DMU-02	3.473	2
3	Supplier-03	DMU-03	2.19	6
4	Supplier-04	DMU-04	3.726	1
5	Supplier-05	DMU-05	1.187	9
6	Supplier-06	DMU-06	3.122	4
7	Supplier-07	DMU-07	1.765	7
8	Supplier-08	DMU-08	2.562	5
9	Supplier-09	DMU-09	3.157	3
10	Supplier-10	DMU-10	0	10

VI. RESULT DISCUSSION AND SENSITIVITY ANALYSIS

A. Result discussion

The evaluation and ranking of suppliers using the integrated IVF-MULTIMOOSRAL methodology, as reported in Table 7, provide an in-depth understanding of each supplier's performance within the oil and gas sector. Supplier-04 stands out as the top performer with a final score of 3.726, highlighting its exceptional efficiency in meeting the company's stringent requirements. Similarly, Supplier-02 and Supplier-09 secured the second and third positions, with scores of 3.473 and 3.157, respectively. Supplier-10 ranked the lowest with a score of 0, indicating significant shortcomings in its ability to meet the necessary criteria. Supplier-05 and Supplier-01 also scored relatively low, with final amounts of 1.187 and 1.628, respectively, placing them in the ninth and eighth positions.

The results in Table 8 provide valuable insights into the performance of different supplier evaluation methodologies and their implications for supplier selection. Comparing traditional MOORA-based methods with their interval-valued fuzzy (IVF) counterparts reveals notable shifts in supplier rankings, suggesting that incorporating fuzzy logic leads to more nuanced assessments of supplier performance. For instance, DMU-02's ranking changes dramatically between traditional and IVF methods, underscoring the importance of considering uncertainty in supplier evaluation. The consistent top performance of DMU-04 across all methods validates its robustness as a supplier, contributing to our understanding of supplier reliability metrics in complex supplier selection scenarios.

Among the various IVF methodologies evaluated, the IVF-MULTIMOOSRAL method stands out for its unique and consistent ranking pattern. It captures complex, multi-criteria decision-making scenarios while accounting for uncertainty more effectively than traditional methods. This is particularly evident in its ability to provide a balanced evaluation across different performance levels. The IVF-MULTIMOOSRAL method demonstrates a promising capacity to offer a comprehensive evaluation, with its nuanced differentiation in rankings suggesting it is a valuable tool for enhancing supplier selection. This method’s alignment with other IVF techniques and its detailed assessment approach offer practical implications for organizations aiming to optimize their supplier choices in uncertain business environments.

While the top and bottom performers show clear and consistent rankings, there is considerable variability among mid-range suppliers. For instance, Supplier-02 demonstrates a notable contrast between traditional methods and the IVF methods. It ranks 8th in both MOORA and MULTIMOORA, but significantly improves to 1st or 2nd in the IVF versions. This variability suggests that Supplier-02's performance may be more accurately captured when accounting for uncertainty and imprecision, revealing its strengths under different evaluative conditions.

The sensitivity of rankings to different methods is also evident, with substantial differences observed for some suppliers. For example, Supplier-07 ranks 4th in the MOORA method but drops to 8th in the MULTIMOORAL method. This variability underscores the importance of selecting an appropriate evaluation method that aligns with the specific context and objectives of the supplier selection process, as different methodologies can lead to markedly different outcomes.

Certain suppliers, such as Supplier-03 and Supplier-09, exhibit relatively stable mid-range rankings across all methods, indicating their consistent, albeit not exceptional, performance regardless of the evaluation approach. This stability suggests that these suppliers are dependable, though they may not stand out under any particular method.

Finally, the impact of fuzzy logic is apparent in the variability of rankings when using IVF methods. For instance, Supplier-01 experiences a slight decline in ranking with IVF methods, while Supplier-02 shows a dramatic improvement. This indicates that incorporating fuzzy logic to account for uncertainty and imprecision can significantly affect how supplier performance is perceived, highlighting the nuanced impact of different evaluation criteria on supplier assessments.

Table 10. Comparison of Supplier Rankings Across Different MCDM Methods

NO.	Symbol Suppliers	MOORA method	MULTIMOORA method	MULTIMOORAL method	IVF-MOORA method	IVF-MULTIMOORA method	IVF-MULTIMOOSRAL method
1	DMU-01	7	7	7	8	8	8
2	DMU-02	8	8	6	1	1	2
3	DMU-03	5	3	3	5	5	6
4	DMU-04	1	2	2	2	2	1
5	DMU-05	9	9	9	9	9	9
6	DMU-06	3	1	1	3	3	4
7	DMU-07	4	5	8	7	7	7
8	DMU-08	2	4	5	4	4	5
9	DMU-09	6	6	4	6	6	3
10	DMU-10	10	10	10	10	10	10

B. Sensitivity analysis

The sensitivity analysis, utilizing a continuous uniform probability distribution for criteria weights over 50 iterations, reveals distinct patterns in supplier performance. The sensitivity analysis reveals significant variations in supplier performance across the 50 test iterations. As shown in Table 9, Supplier-04 demonstrates remarkable consistency, ranking first in 34 out of 50 tests and never falling below 4th place. In contrast, Supplier-10 consistently underperforms, ranking last in 45 tests and never rising above 9th place (Table 9). This stark difference in performance stability is clearly illustrated in the rank distribution graphs for Supplier-04 and Supplier-10 (Figure 2).

Suppliers in the middle range exhibit considerable ranking volatility. For instance, Supplier-03 fluctuates between 2nd and 9th place across the tests. Similarly, Supplier-06 oscillates between 1st and 6th rank. This variability suggests that these suppliers' performances are highly sensitive to changes in criteria weights, indicating potential areas for improvement in their overall capabilities (Figure 5).

Some suppliers display interesting outlier performances. Supplier-02, while generally performing well (often in the top 3), occasionally drops to significantly lower rankings, such as 5th place in Test 5 (Table 9). This pattern, visible in Figure 4, suggests that while Supplier-02 is generally strong, it may have specific weaknesses that become apparent when certain criteria are weighted more heavily.

The analysis reveals frequent rank reversals between certain suppliers. For example, Supplier-07 and Supplier-09 often swap positions across different tests (Table 9). This indicates that their relative performance is particularly sensitive to changes in criteria weights. Additionally, some suppliers tend to cluster in specific ranking ranges. Supplier-01, for instance, frequently appears in the 6th to 8th rank range, while Supplier-05 often occupies the 7th to 9th positions (Figure 5).

Despite the observed variations, there is a degree of overall stability in the rankings. The top performers (Supplier-04, Supplier-02) and bottom performers (Supplier-10) remain relatively consistent across most tests (Table 9). This suggests that while specific weights of criteria do impact rankings, there are fundamental differences in supplier capabilities that persist across various evaluation scenarios. The graphs for these suppliers (Figure 4) visually reinforce this stability. This finding underscores the importance of comprehensive supplier evaluation processes that consider performance across multiple criteria and scenarios.

Table 11 Supplier Rankings Across 50 Test Iterations

Suppliers	Supplier-01	Supplier-02	Supplier-03	Supplier-04	Supplier-05	Supplier-06	Supplier-07	Supplier-08	Supplier-09	Supplier-10
Test 1	8	2	6	1	9	4	7	5	3	10
Test 2	5	1	7	2	4	3	9	8	6	10
Test 3	8	3	7	1	9	4	6	5	2	10
Test 4	7	1	5	2	8	3	9	6	4	10
Test 5	7	5	8	1	9	4	3	6	2	10
Test 6	8	2	4	1	7	3	9	6	5	10
Test 7	7	4	2	1	5	3	9	8	6	10
Test 8	4	1	8	3	6	5	9	7	2	10
Test 9	8	3	5	1	9	2	4	6	7	10
Test 10	7	3	5	1	9	2	8	6	4	10
Test 11	8	1	6	2	7	4	9	5	3	10
Test 12	6	1	5	2	4	3	9	8	7	10
Test 13	5	1	7	2	8	3	9	6	4	10

Continue Table 12. Supplier Rankings Across 50 Test Iterations

Suppliers	Supplier-01	Supplier-02	Supplier-03	Supplier-04	Supplier-05	Supplier-06	Supplier-07	Supplier-08	Supplier-09	Supplier-10
Test 14	6	2	4	1	7	3	9	8	5	10
Test 15	7	1	6	3	8	2	9	5	4	10
Test 16	7	3	5	1	6	2	9	8	4	10
Test 17	7	1	6	2	5	4	8	9	3	10
Test 18	6	1	7	2	5	4	10	8	3	9
Test 19	7	3	5	1	9	2	8	6	4	10
Test 20	6	2	7	1	8	3	9	5	4	10
Test 21	4	1	7	2	5	3	9	8	6	10
Test 22	7	2	6	1	5	3	9	8	4	10
Test 23	7	3	5	1	8	2	9	6	4	10
Test 24	8	2	6	1	9	3	5	7	4	10
Test 25	7	4	6	1	8	3	10	5	2	9
Test 26	8	2	6	1	7	3	9	5	4	10
Test 27	9	4	5	1	7	2	6	8	3	10
Test 28	8	1	7	3	9	2	6	4	5	10
Test 29	7	2	4	3	8	1	9	6	5	10
Test 30	8	2	7	1	10	4	6	5	3	9
Test 31	7	1	6	3	8	2	9	5	4	10
Test 32	6	2	8	1	7	3	9	5	4	10
Test 33	7	1	8	4	9	3	6	5	2	10
Test 34	6	1	5	4	7	3	9	8	2	10
Test 35	5	3	6	1	8	2	10	7	4	9
Test 36	7	1	6	2	9	3	8	5	4	10
Test 37	7	1	5	2	8	6	4	9	3	10
Test 38	7	3	5	1	9	2	8	6	4	10
Test 39	8	1	3	7	4	2	9	5	6	10
Test 40	7	3	4	1	9	2	8	5	6	10
Test 41	8	3	5	1	9	2	7	6	4	10
Test 42	6	1	8	3	7	4	9	5	2	10
Test 43	7	2	5	1	8	3	9	6	4	10
Test 44	7	1	9	3	6	2	8	4	5	10
Test 45	4	3	7	1	6	2	9	8	5	10
Test 46	9	4	6	1	7	3	2	8	5	10
Test 47	8	1	4	2	9	3	7	6	5	10
Test 48	6	1	7	4	8	2	9	5	3	10
Test 49	7	1	5	2	8	3	9	6	4	10
Test 50	7	4	3	1	8	2	9	6	5	10

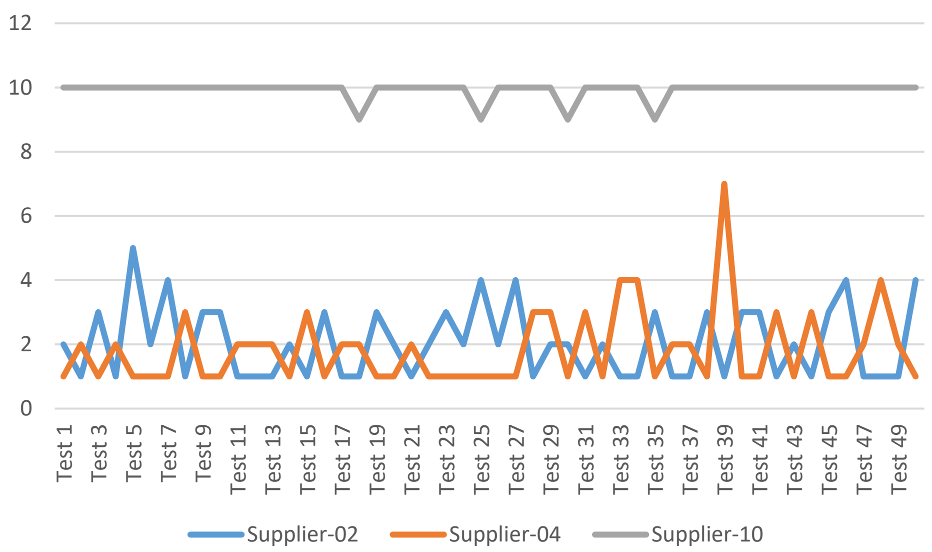

Figure 3 Rank Distribution of Supplier-02, Supplier-04, and Supplier-10 Across 50 Tests

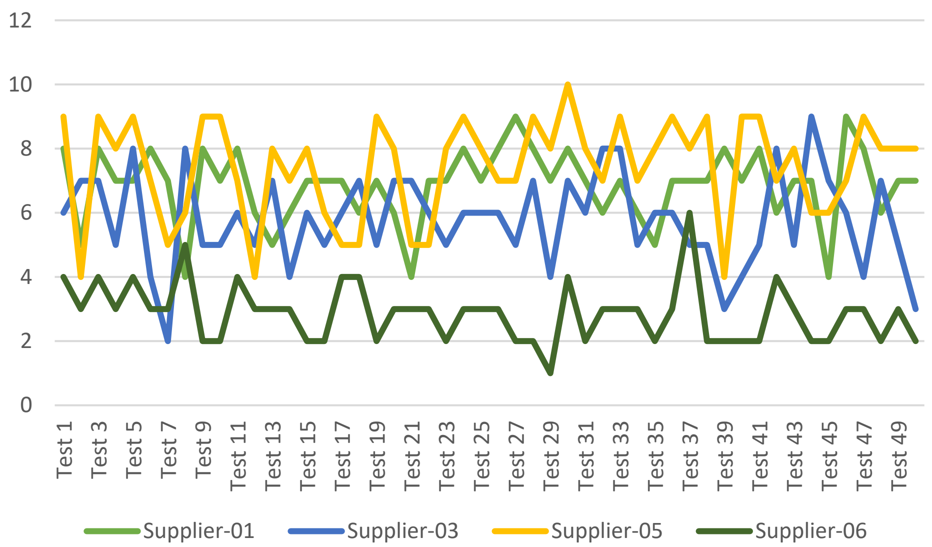

Figure 4 Rank Distribution of Supplier-01, Supplier-03, Supplier-05, and Supplier-6 Across 50 Tests

VII. CONCLUSION

The IVF-MULTIMOOSRAL approach in this study offers a flexible framework for supplier selection in the oil and gas industry. By incorporating IVFSs, the method effectively addresses the inherent uncertainties in supplier evaluation processes. The case study and sensitivity analysis demonstrate the method's ability to provide consistent rankings for top and bottom performers while revealing nuanced differences among mid-range suppliers under varying criteria weights. The results highlight the importance of comprehensive evaluation methods that can capture the complexities of supplier performance across multiple criteria. The consistent high ranking of Supplier-04 and low ranking of Supplier-10 across different methodologies and sensitivity tests underscore fundamental differences in supplier capabilities that persist across various evaluation scenarios. However, the variability observed in mid-range supplier rankings emphasizes the need for careful consideration of evaluation criteria and their weights. This variability also suggests potential areas for improvement among these suppliers, which could be valuable information for both the purchasing company and the suppliers themselves. The proposed IVF-MULTIMOOSRAL method contributes to the field of supplier selection by offering a more nuanced approach to handling uncertainty and imprecision in decision-making. Its application can lead to more informed and reliable supplier choices in the oil and gas industry, potentially improving supply chain efficiency and effectiveness. Future research could explore the application of this method in other industries or compare its performance with other advanced MCDM techniques. Additionally, incorporating more dynamic factors, such as supplier improvement potential or long-term relationship value, could enhance the method's practical utility in strategic supplier selection processes. The IVF-MULTIMOOSRAL method contributes meaningfully to supplier selection by offering a sophisticated approach to managing uncertainty and imprecision in decision-making. Its application can lead to more informed and reliable choices, potentially enhancing supply chain efficiency and effectiveness in the oil and gas industry.

Future research could refine this method by exploring new fuzzy methodologies to improve precision, integrating gray relational analysis to enhance decision-making, adjusting normalization techniques for better optimization, and incorporating interval and gray approaches to increase robustness (e.g. Behzadipour et al., 2022; Mousavi et al., 2016; Mahmoudian Azar Sharabiani and Mousavi, 2023; Dorfeshan et al., 2023; Jahangirzadeh et al., 2020; Salimian et al., 2023; Salimian and Mousavi, 2023). Additionally, combining different approaches within the method could leverage their collective strengths, leading to improved overall performance.

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