Sustainable Operations: Well Selection in Oil and Gas Projects

Abstract

Purpose

This study aims to enhance decision-making in the selection of oil and gas (OG) wells for stimulation operations by integrating sustainability into project management practices. By proposing an innovative multi-criteria decision-making (MCDM) framework, the research seeks to improve production efficiency while considering economic and environmental factors.

Design/methodology/approach

The proposed framework employs an interval-valued spherical fuzzy (IVSF) entropy method to determine the weights of fourteen critical criteria from both engineering and managerial perspectives. Four fuzzy ranking methods are then applied to evaluate well selection strategies, with the results aggregated using the Borda method. A sensitivity analysis is conducted to assess the robustness of the approach, particularly in mitigating risks associated with economic forecasts for carbonate reservoirs.

Findings

The study demonstrates that the proposed MCDM-based framework enhances decision-making by providing a structured and transparent evaluation of OG well selection. The integration of sustainability-focused criteria ensures alignment with project objectives while improving economic viability. The sensitivity analysis confirms the reliability of the method, indicating its effectiveness in addressing uncertainties in economic forecasts and operational risks.

Originality/value

This research presents a novel approach that bridges project management innovation with sustainable well selection in the OG industry. By leveraging IVSF entropy and multiple fuzzy ranking techniques, the study introduces a more comprehensive and resilient decision-making model. The findings offer practical implications for both technical and managerial stakeholders, supporting more informed, efficient, and sustainable OG reservoir management.

Keywords: Hydrocarbon Reservoirs; Oil and Gas; Well Selection; Project Management; Multiple criteria decision making; Entropy

1. Introduction

Investment in energy transition activities and processes is increasing due to technological advancements, the growing demand for resources and transportation, and a rising global population. In 2022, approximately 13% of total investments by leading companies such as BP, Chevron, and Shell were allocated to sustainable energy projects, representing a 42% increase compared to 2021 (Sia Partners, 2023). This trend is evident across many companies implementing systems, processes, and operations to reduce greenhouse gas (GHG) emissions. For instance, between 2019 and 2023, Murphy Oil reduced its GHG emissions intensity by 37%, methane intensity by 51%, and flaring intensity by 66%, aligning with its 2030 goals of achieving zero routine flaring and further reducing GHG intensity by 15% to 20% (Murphy Oil Corporation, 2023).

In line with this development, the role of sustainability in project management within the oil and gas (OG) industry is becoming increasingly significant. Project managers should aim to integrate sustainability into all aspects of their projects, from resource management to stakeholder engagement. This approach extends beyond traditional goals like time and cost efficiency to include environmental metrics and minimizing ecological impacts (Silvius & Schipper, 2014).

In 2024, the oil and gas (OG) industry is expected to maintain a strong focus on decarbonization initiatives, with companies striving to balance core operations while investing in cleaner energy technologies. Notably, the U.S. Environmental Protection Agency (EPA) mandates industries to adopt technologies that detect and reduce methane emissions (L.E.K.

Consulting, 2024). Digital transformation plays a pivotal role in enhancing sustainability within project management in the OG sector. By adopting project management software and integrating digital tools such as IoT and advanced analytics, companies are improving efficiency, reducing costs, and minimizing environmental impact. These technologies facilitate real-time data collection and analysis, enabling project teams to make informed decisions that align with sustainability goals (ScheduleReader, 2024).

Projects are fundamental to a company's growth and success (Muhsen et al., 2024).They encompass a range of activities and processes that drive the development of innovative products and services, as well as the enhancement of operational procedures.

Oil and gas (OG) projects are typically categorized into three main segments: upstream, midstream, and downstream. Upstream projects include activities related to exploration, development, production, enhanced oil recovery, and the decommissioning of platforms. Midstream projects involve the transportation, storage, and processing of petroleum, covering pipeline operations, processing plants, terminals, and ports. Downstream projects focus on refining and distributing oil and gas products, involving crude oil pipelines, natural gas pipelines, oil storage terminals, liquefied natural gas (LNG) plants, and gas processing facilities (Dartey-Baah et al., 2023).

All types of projects in the OG industry, particularly those related to exploration and production, are inherently hazardous and often highly complex due to significant political, environmental, and ecological uncertainties. These uncertainties contribute to the high levels of risk commonly associated with OG projects (Ishtiaq et al., 2023). Investments in OG projects are vulnerable to potential losses stemming from technical, economic, and political risks. For instance, drilled oil wells may encounter numerous technical challenges, while economic risks can arise from geopolitical conflicts, regulatory changes, or currency fluctuations. Additionally, political risks can further exacerbate the vulnerability of these investments (Dartey-Baah et al., 2023).

Consequently, the application of project management principles is essential. Emphasis should be placed on robust risk assessment and the implementation of effective mitigation strategies to address these complexities.

The strategic adoption of project management plays an indispensable role for businesses striving to maintain a cutting-edge business environment (Demir & Turan, 2021; Secundo et al., 2022). Effective project management not only drives sales and cuts costs but also raises the standard level of products and customer satisfaction (Alnoor et al., 2022; Muhsen et al., 2024).The growing awareness of these advantages prompts many companies to adopt project management strategies, significantly boosting their ability to create value (Lewis, 2000; Salazar-Aramayo et al., 2013). Project management can be defined as the use of methods, skills, knowledge, and experience to achieve predefined goals of the project and adhere to the project's acceptance criteria. Project management concepts can integrate miscellaneous disciplines and domains by adopting a problem-solving approach. Collaborating closely within a team facilitates a shared understanding, bridging the gaps between expertise and approaches (Lyandau, 2022; Marion & Richardson, 2022).

One of the critical industries where project management plays a vital role is oil and gas (OG). This sector faces various challenges, including price fluctuations. However, a significant issue lies in the efficient improvement of recovery rates in mature oil fields (Aliasser & Adesta, 2021; Dartey-Baah et al., 2023). This challenge has become increasingly pressing due to the depletion of OG resources and the rising energy demand. Effective project management is essential for advancing recovery techniques while ensuring economic viability and environmental sustainability. These factors highlight the critical importance of adept project management in navigating the complexities of identifying and developing new reservoirs.

Within this context, hydraulic fracturing (HF) emerges as a pivotal stimulation technique for boosting hydrocarbon recovery. Its application extends beyond conventional wells to include unconventional sources such as tight gas and shale gas, showcasing significant potential in overcoming the inherent challenges of carbonate reservoirs. The success of HF treatments depends on comprehensive project management, encompassing candidate-well selection (CWS), treatment design, and field operations. Among these, the strategic selection of appropriate wells is particularly critical, offering fertile ground for research and innovation. This process not only addresses the technical challenges associated with HF but also aligns with broader project management objectives to ensure sustainable and efficient resource development (Yu et al., 2016; Zoveidavianpoor & Gharibi, 2016; Zoveidavianpoor et al., 2013). By emphasizing project management principles, practitioners in the oil and gas (OG) sector can more effectively navigate the complexities of enhancing recovery rates, particularly within the industry's evolving energy landscape.

In the realm of HF treatment, the success or failure of the process largely depends on the quality of the selected candidate well. To achieve a successful outcome, it is essential to choose an appropriate OG well with a lower risk profile and higher recovery potential. Conversely, selecting a poor candidate well can result in a failed HF process (Malik et al., 2006; Vincent, 2011). The selection of an appropriate well is a complex process, influenced by uncertainties that arise during the development and production stages. These uncertainties are primarily attributed to two key factors: structure-oriented and economic-oriented. The former includes considerations such as reservoir sealing and hydrocarbon charge, while the latter encompasses oil prices, probability of discovery, and the economic viability of producing reservoirs. Despite the significant uncertainties involved, a comprehensive and reliable method for candidate well selection across varying situations has yet to be established (Farid et al., 2023).

When addressing the complexity of decision-making in HF issues, multiple criteria decision-making (MCDM) methods, as discussed by (Storch de Gracia et al., 2019), offer an effective means to evaluate alternative solutions. This is particularly crucial when some parameters are qualitative and based on expert knowledge. A notable challenge in this domain is the selection of candidate OG wells, which involves a wide range of criteria, many of which cannot be precisely defined or quantified, complicating the identification of the optimal solution. Two key factors influencing this problem are managerial and engineering considerations. Managerial factors, derived from expert opinions, pertain to general project conditions and are inherently difficult to quantify. In contrast, engineering factors focus on technical aspects that are directly linked to the alternatives. These two factors provide distinct yet complementary insights for decision-makers; however, comprehensive studies addressing both simultaneously remain scarce. To bridge this gap, this paper proposes an MCDM approach that incorporates uncertainties and employs a linguistic representation of criteria weights using fuzzy numbers. While this approach presents a promising solution, further research is needed to investigate other robust non-deterministic methodologies.

Moreover, the ranking of different MCDM methods for a specific problem may vary (Quaiser & Srivastava, 2024). This variability in outcomes can be attributed to the diverse mathematical techniques employed in MCDM (Yazdani et al., 2019), making it challenging to select a preferred method in advance. Consequently, a single prioritization approach may not be sufficiently robust (Modibbo et al., 2022; Quaiser & Srivastava, 2024). To address this issue, decision-makers often apply multiple methods to determine whether a particular solution (alternative) consistently emerges as the top-ranked option. This approach enhances the robustness of the results and provides comprehensive insights for decision-making. In this study, we employ four fuzzy MCDM methods to achieve this objective: the interval-valued spherical fuzzy additive ratio assessment (IVSFS-ARAS), interval-valued spherical fuzzy complex proportional assessment (IVSFS-COPRAS), interval-valued spherical fuzzy multi-objective optimization by ratio analysis (IVSFS-MOORA), and interval-valued spherical fuzzy method for order preference by similarity to ideal solution (IVSFS-TOPSIS).

When applying MCDM methods, determining the weightings of criteria is a critical issue that can significantly influence the results (Wang & Luo, 2010) . The literature identifies two main approaches for estimating criteria weights: subjective and objective-based methods (Wang & Lee, 2009). In the subjective approach, decision-makers rely on their own judgments to assign weights to criteria. In contrast, the objective approach uses quantitative information and mathematical models, such as entropy, cross-cultural success dimensions (CCSD), and the quantitative strategic planning matrix (QSPM), to calculate the weights. Objective-based methods are particularly valuable when decision-makers lack sufficient knowledge or experience, as they reduce the impact of subjective judgment or intuition on the weighting process.

This study proposes a method that integrates expert experience and professional knowledge to enhance the selection process for carbonate reservoirs. The method aims to eliminate communication barriers between geologists and reservoir engineers while providing an alternative to numerical reservoir simulation by significantly reducing the required database size. Notably, this paper applies the IVSFS-ARAS (Aydoğdu & Gül, 2022), IVSFS-COPRAS (Omerali & Kaya, 2022), IVSFS-MOORA (Aydın & Kutlu Gündoğdu, 2021), and

IVSFS- TOPSIS (Kutlu Gündoğdu & Kahraman, 2019) methods to the well selection field for the first time.

Each of the selected methods has demonstrated robustness in various decision-making scenarios, particularly in multi-criteria decision analysis (MCDA). Their versatility enables them to effectively handle diverse types of data and criteria, making them well-suited for addressing the complexities inherent in reservoir selection. By combining these methods, we leverage their unique strengths. For example, while TOPSIS focuses on proximity to the ideal solution, ARAS emphasizes the ranking of alternatives based on their performance. This complementary approach provides a more comprehensive evaluation of potential reservoirs.

Our primary objective is to bridge the gap between geologists and reservoir engineers. These methods facilitate a structured decision-making framework that is both easily understood and effectively communicated across disciplines. This reduces misunderstandings and fosters collaboration. Additionally, the selected methods are designed to perform well with smaller datasets, aligning with our goal of significantly reducing database size compared to traditional numerical reservoir simulations. Such efficiency is essential for practical applications in the field.

The oil and gas (OG) sector is closely connected to sustainability challenges; however, current research lacks a comprehensive focus on both managerial and engineering factors within this context. Most previous studies have concentrated on a single aspect, with a limited number of articles addressing either engineering factors (Gutor et al., 2003; Habibnia & Shadizadeh, 2009; Howard & Fast, 1970; Shadizadeh et al., 2009) or managerial factors (Ebrahimnejad et al., 2009; Gardas et al., 2019). This study is therefore novel in its approach, as it examines both managerial and engineering dimensions to identify comprehensive factors related to sustainability in the OG sector. The contributions of the paper are summarized as follows:

- A comprehensive MCDM framework is proposed, utilizing IVSFS integrated with an entropy-based weighting mechanism, based on the project management standards and academic research for informed decision-making, ensuring robust handling of uncertainties in the HF well selection process and enhances decision-making processes under uncertainty.

- The framework incorporates a dual perspective by evaluating managerial factors (e.g., regulatory pressure, sustainability, and political stability) alongside engineering factors (e.g., reservoir pressure, well completion method, and production method). This study offers comprehensive approach addresses the multifaceted challenges in HF well selection.
- The study utilizes an innovative ranking method that effectively demonstrates its robustness. Four MCDM techniques, including ARAS, COPRAS, MOORA, and TOPSIS, adapted to interval-valued spherical fuzzy sets for comprehensive evaluation. The Borda method is used to aggregate the rankings from these methods, ensuring methodological robustness and reducing reliance on a single prioritization technique.
- The proposed methodology is empirically validated through a case study involving seven wells in three Iranian carbonate reservoirs, demonstrating its practical applicability in selecting optimal wells for HF treatment in complex geological and operational contexts.
- By emphasizing sustainability metrics and economic viability in the evaluation process, the framework aligns with contemporary goals of reducing environmental impacts in the OG sector. It provides actionable insights for practitioners to balance production efficiency with ecological responsibility.
- Highlighting critical criteria in order to guild managers and decision-makers in applying and formulating strategies. This ensures the robustness and reliability of the proposed decision-making approach.

This paper is organized as follows: Section 2 provides a comprehensive literature review of well selection and MCDM methods, discussing the influential factors in candidate well selection and their implications for project management in both academia and industry. In Section 3, we present our proposed model for well selection, outlining its stages and explaining each in detail, with an emphasis on its relevance to academic research and project management practices. Section 4 illustrates the practical application of our model through a real-world case study, integrating theoretical perspectives with project management insights to validate key academic concepts. Section 5 focuses on sensitivity analysis, examining the impact of varying input parameters on the model's outcomes and presenting a thorough analysis of the results, highlighting their academic and project management implications. Section 6 discussed the theoretical, managerial, and policy implications, and finally, Section 7 provides concluding remarks and suggestions for future research directions in well selection, MCDM, and project management, aiming to bridge the gap between academic research and practical application in the oil and gas industry.

2. Literature review and associated background

2.1. Candidate OG well selection

The methodologies implemented for HF candidate well selection could be categorized in two parts, i.e. conventional techniques that cover the engineering or geological aspects in the decision-making process; and advanced methods which consider the classification and setting of affecting parameters mostly by Artificial Intelligence (AI) methods (Zoveidavianpoor et al., 2012).

The methodologies implemented for HF candidate well selection can be categorized into two parts: conventional techniques, which address the engineering or geological aspects of the decision-making process, and advanced methods, which involve the classification and prioritization of influencing parameters, primarily using Artificial Intelligence (AI) techniques (Zoveidavianpoor et al., 2012).

In the field of candidate well selection, the inherent nonlinearity and uncertainty in datasets make them ambiguous and imprecise. Consequently, researchers have employed advanced methods to address these challenges (Yu et al., 2016). For example, Yang et al. (2006) developed a novel prediction method for fracturing effects using a support vector machine, which conducted a comprehensive analysis of relevant parameters. Furthermore, Guo et al. (2014) proposed an enhanced reservoir evaluation index system by incorporating fuzzy logic theory and a multilevel grey analysis (GRA)-based model for gas well reservoirs.

Moreover, the challenge of selecting candidate wells shares many common characteristics with other environmental problems, such as water resource planning (Weng et al., 2010), environmental management (Sánchez-Lozano & Bernal-Conesa, 2017), and energy management (Çolak & Kaya, 2017).

2.2. Multiple criteria decision-making methods

In recent years, the use of Multi-Criteria Decision-Making (MCDM) methods has become increasingly prevalent in addressing decision-making challenges related to sustainable energy (Konstantinos et al., 2019). This trend can largely be attributed to the ability of MCDM methods to account for the inherent complexity of socio-economic and biophysical systems, as well as the multidimensional nature of sustainability-related issues. However, despite their growing popularity, the application of MCDM methods is not without challenges and limitations that warrant critical examination.

In practice, MCDM methods have been applied in various contexts, including risk-based decision-making problems such as maintenance strategies for identifying factors contributing to failures in oil and gas pipelines, as well as project portfolio selection in energy resources (Wang et al., 2009). For example, Lev (2007) introduced several MCDM methodologies, including the Analytic Hierarchy Process (AHP), the Multi-Attribute Utility Theory (MAUT), and the Simple Multi-Attribute Rating Technique (SMART), which have been effectively utilized for petroleum project selection. While these methodologies have proven effective, they often rely heavily on subjective judgments, which can introduce bias and variability, especially in complex decision-making scenarios.

The study of environmentally oriented MCDM problems has been the focus of several academic investigations. One such study, conducted by Sánchez-Lozano et al. (2016) employed the fuzzy TOPSIS method to identify suitable sites for onshore wind farms, demonstrating how fuzzy adaptations of various MCDM methods, such as fuzzy AHP and fuzzy TOPSIS, can be combined to achieve more accurate results. While this combination enhances precision, it also complicates the decision-making process, potentially reducing the transparency and interpretability of the results—factors that are critical for stakeholder engagement in environmental projects. Furthermore, Liu et al. (2018) conducted a study using the ANP-SWOT methodology to evaluate industry strategies in the Chinese building sector, demonstrating the effectiveness of this approach in addressing complex problems in real-world scenarios. Namin et al. (2022) review Mining Method Selection (MMS) approaches, which represent one of the most important decisions in mine design. They show that AHP and TOPSIS are the most commonly used methods for selecting mining methods. Shekar et al. (2025) use five MCDM methods to prioritize sub-watersheds for effective resource management aimed at mitigating soil erosion and ranking erosion zones that require urgent intervention. Recent studies have shown that morphometric analysis combined with MCDM methods like VIKOR, TOPSIS, and SAW can effectively prioritize erosion-prone sub-watersheds, offering valuable insights for sustainable soil and water management (El Abassi et al., 2024). In the context of Iran's oil and gas industry, recent research has emphasized the need for advanced decision-making tools to enhance service supply chain performance, using fuzzy SWARA and MABAC methods to uncover critical capabilities and optimal service locations (Mehdiabadi et al., 2025). Lately, to enhance supplier selection in the oil and gas sector, recent studies have applied fuzzy AHP and TOPSIS methods, effectively integrating expert-validated criteria to support more balanced and data-driven decision-making .(Abdollahi Kamran et al., 2025)

However, the integration of multiple methodologies can introduce methodological complexity, potentially hindering practical application and decision-making clarity. Gul and Ak (2021) applied interval-valued spherical fuzzy sets to extend the method for order preference by similarity to the ideal solution (IVSF-TOPSIS), addressing limitations in traditional risk priority number (RPN) calculations. This approach modified the Failure Modes and Effects Analysis (FMEA) framework to evaluate potential failures in product or process design. While this advancement highlights innovation in fuzzy MCDM applications, it also raises concerns about increased complexity and the risk of overfitting models to specific datasets. Jin et al. (2021) developed a three-dimensional house of quality using an interval-valued spherical fuzzy adaptation of the classical ORESTE method to rank key quality characteristics and determine product quality levels. Similarly, in the healthcare sector, Kutlu Gündoğdu and Kahraman (2021) proposed an interval-valued spherical fuzzy version of the AHP for comparing the service performance of several hospitals. These applications demonstrate the versatility of fuzzy MCDM methods; however, they also highlight the

importance of critically evaluating how effectively these methods address the unique challenges of each sector.
The preceding studies suggest that the practical application of fuzzy MCDM methods is an effective approach to solving complex environmental problems. MCDM provides a valuable framework for developing systematic methodologies to rank environmental projects, which often involve diverse objectives and constraints that must satisfy socio-political conditions. However, as Mulliner et al. (2016) noted, these objectives can be non-commensurable and conflicting, further complicating the decision-making process.

Despite the extensive exploration of MCDM models across various contexts, a notable gap remains in the literature regarding their application for candidate well selection and prioritization. This gap highlights the need for further research to adapt and refine MCDM methodologies specifically for the oil and gas sector, ensuring that the unique complexities and uncertainties of well selection are effectively addressed.

2.3. Effective criteria in candidate OG well selection

To aid in the selection of candidate wells, various criteria have been suggested by different authors. Howard and Fast (1970) have identified nine engineering factors that are crucial for candidate well selection. However, engineering factors have predominantly been the focus of research in this area. Recent studies by Shadizadeh et al. (2009), and Habibnia and Shadizadeh (2009) have emphasized the significance of rock formation mechanical properties, remaining reserves, petrophysical properties, and stress profiling in identifying the key factors for candidate well selection. Furthermore, Gutor et al. (2003) found that the age of the well has little effect on selecting re-stimulation candidates.

While these studies have primarily focused on engineering factors, other relevant aspects have been generally overlooked. To address this gap, this paper presents a research methodology for risk assessment of offshore wells, with a comprehensive approach that takes into account all relevant factors. In addition to what mentioned above, specific factors such as the role of regulatory compliance (Mwelu et al., 2020), stakeholder engagement (Silvius & Schipper, 2019), and risk management as managerial factors (Schieg, 2006), alongside engineering considerations like enhanced oil recovery techniques (Zeqiraj, 2022), environmental impact assessments (Vilardo & La Rovere, 2018), and the adoption of cleaner technologies (Ikram et al., 2021) can provide a clearer picture of the current research landscape and highlight the gaps that our study seeks to address.

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Several other important studies primarily address managerial issues. Gardas et al. (2019) identified collaborative logistics and regulatory pressure as the most significant factors influencing the oil and gas (OG) sector. Ebrahimnejad et al. (2009) highlighted managerial factors, such as economic risks and political stability, as key elements impacting OG projects.

Given the nature of Iranian hydrocarbon reservoirs, which predominantly consist of fractured carbonate rock types, decision-making committees prioritize specific parameters from the aforementioned ones that are most relevant to the Iranian candidate well selection problem.

The following table (Table 1) illustrates the mentioned parameters and their effect on candidate selection. It is worth noting that some of the main criteria include several sub-parameters, represented in Table 1.

Table 1. The affecting criteria information (Table by Authors)

Type of factor	Criteria		Notation	Effect	References
Engineering	Water Cut		C_1	Negative	(JIANG et al., 2004)
Managerial	Collaborative Logistics		C_2	Positive	(Chima, 2007; Palmieri et al., 2019; Saad et al., 2014)
Engineering	Operational Parameters		C_3	Negative	(KEk et al., 2022; Salamai et al., 2019)
Managerial	Regulatory Pressure		C_4	Negative	(Khan et al., 2021; Liu et al., 2022)
Managerial	Economic and financial risks		C_5	Negative	(Cheng et al., 2019)
Engineering	Well Direction	• Horizontal • Directional • Vertical	C_6	Positive	(Khan et al., 2021)
Managerial	Environment and Sustainability		C_7	Positive	(Cheng et al., 2019; Edoho, 2008)
Engineering	Well Completion Method	• Open hole • In same direction • In opposite direction • Intermediate	C_8	Positive	(Ma et al., 2020; Zhang et al., 2011)

Type of factor	Criteria		Notation	Effect	References
Managerial	Political stability		C_9	Positive	(Cheng et al., 2019; Doukas et al., 2011)
Engineering	Sand Production		C_{10}	Positive	(Pham, 2017)
Engineering	Production Method	• Naturally Flow • Artificial lift • Dead Wells	C_{11}	Positive	(Yehorchenkova & Yehorchenkov, 2020)
Engineering	Reservoir Pressure		C_{12}	Positive	(Pathak, 2021)
Managerial	Resource Risks		C_{13}	Negative	(Cheng et al., 2019; Farrell & Brandt, 2006)
Engineering	Field Type	• Offshore • Onshore	C_{14}	Positive	(Elkholosy et al., 2024)

3 Problem definition and solving methodology

The well selection problem is a strategic issue in natural OG exploitation, and its operational success depends on the proper selection of target well and target formation. On the other hand, selecting the optimal well among many alternatives could address an MCDM problem.

In literature, weights of criteria in an MCDM problem could be calculated subjectively and objectively (Wang & Lee, 2009). While subjective methods find the criteria weights exclusively based on the preference or judgment of decision-makers, objective methods take advantage of specific mathematical models.

Objective weighting could be known as a well-suited approach for decision-making problems that deal with primarily quantitative information. Therefore, we implemented the entropy-based weighting procedure, through which weights are not affected by the subjective judgment and intuition of the decision-maker.

The well selection problem is a strategic issue in OG exploitation, where operational success depends on the proper selection of the target well and formation. Selecting the optimal well from multiple alternatives constitutes a multi-criteria decision-making (MCDM) problem.

In the literature, the weights of criteria in an MCDM problem can be calculated either subjectively or objectively (Wang & Lee, 2009). Subjective methods determine criteria weights based solely on the preferences or judgments of decision-makers, while objective methods rely on specific mathematical models.

Objective weighting is particularly well-suited for decision-making problems that primarily involve quantitative information. Therefore, we employed an entropy-based weighting procedure, which ensures that weights are unaffected by the subjective judgments and intuitions of the decision-maker.

The entropy method (Shannon, 2001) is based on the idea that the importance of a criterion can be derived from its relativity to the entire set of alternatives. This means that a greater impact on the evaluations of the alternatives results in higher importance (Singh & Benyoucef, 2011). The advantages of the entropy method over other weighting methods stem from the elimination of decision-maker subjectivity in determining weights. It is particularly useful in cases where decision-makers disagree on priorities. In other words, objective weights derived through entropy can be used to adjust subjective weights assigned by decision-makers (Shemshadi et al., 2011).

The application of MCDM methods in selecting candidate wells has often been overlooked. Relying solely on a single prioritization method can lead to inconsistent rankings due to the inherent characteristics of MCDM methods. To address this limitation, decision-makers frequently employ multiple MCDM methods with low correlation to enhance the robustness of results, mitigate the shortcomings of individual models, and provide a comprehensive perspective for decision-making. In this context, the IVSFS-ARAS, IVSFS-COPRAS, IVSFS-MOORA, and IVSFS-TOPSIS methods were selected for their relatively low correlation, which aids in effectively prioritizing alternatives. This paper proposes a comprehensive methodology, illustrated in Figure 1, which comprises three main components: group work, criteria weighting, and alternative evaluation.

This methodology rigorously evaluates fourteen criteria from both engineering and managerial perspectives, achieving a balance between sustainability and economic viability. The IVSF entropy method efficiently determines the significance of each criterion, thereby improving the management of uncertainties inherent in expert judgments. By incorporating multiple fuzzy ranking methods, the approach offers diverse strategic perspectives, which is particularly valuable when wells demonstrate similar viability. The Borda count method further enhances decision accuracy by consolidating these rankings, ensuring that the final decision aligns closely with project objectives. Additionally, sensitivity analysis is conducted to evaluate the stability of outcomes under varying assumptions, a critical factor for reliable decision-making in complex reservoir environments. The integration of advanced fuzzy logic, robust ranking methodologies, and sensitivity analyses not only strengthens decision-making in the oil and gas sector but also supports strategic management and sustainability goals. Notably, this approach utilizes interval-valued spherical fuzzy sets, which provide flexible definitions of membership functions presented as intervals based on expert judgments.

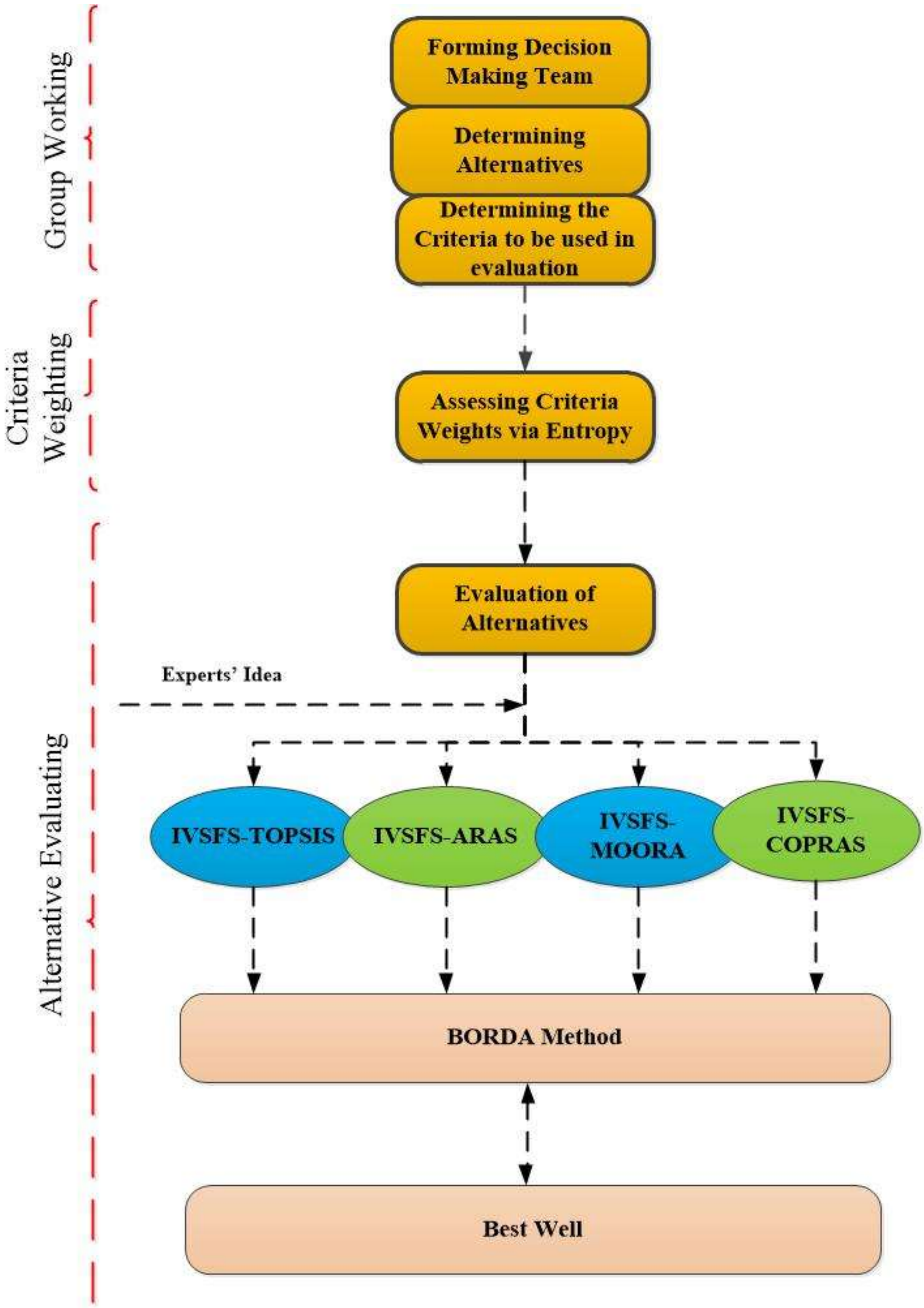

Figure 1. Diagram of the proposed model for well selection (Figure by Authors)

3.1. Interval-valued spherical fuzzy sets

This part is devoted to presenting the definition of Interval-valued spherical fuzzy sets (IVSFS), arithmetic operations, distance measurement, and the method of defuzzification. An IVSFS $\widetilde{X_s}$ $\tilde{X}_s$is defined as follows:

$$\widetilde{X_s} = \left\{ \left\langle u, \left(\left(\left[\mu^L_{\widetilde{X_s}}(u), \mu^U_{\widetilde{X_s}}(u) \right], \left[\upsilon^L_{\widetilde{X_s}}(u), \upsilon^U_{\widetilde{X_s}}(u) \right], \left[\pi^L_{\widetilde{X_s}}(u), \pi^U_{\widetilde{X_s}}(u) \right] \right) \middle| u \in U \right) \right\} \quad (1)$$

$$0 \leq \mu^L_{\widetilde{X_s}}(u) \leq \mu^U_{\widetilde{X_s}}(u) \leq 1 \quad (2)$$

$$0 \leq \upsilon^L_{\widetilde{X_s}}(u) \leq \upsilon^U_{\widetilde{X_s}}(u) \leq 1 \quad (3)$$

$$\left(\mu^U_{\widetilde{X_s}}(u) \right)^2 + \left(\upsilon^U_{\widetilde{X_s}}(u) \right)^2 + \left(\pi^U_{\widetilde{X_s}}(u) \right)^2 \leq 1 \quad (4)$$

In which $\mu^U_{\widetilde{X_s}}(u)$, $\upsilon^U_{\widetilde{X_s}}(u)$ and $\pi^U_{\widetilde{X_s}}(u)$ are upper degrees of membership, non-membership and hesitancy. Furthermore, in the following conditions, the IVSFS will reduce to a single valued SFS.

$$\mu^L_{\widetilde{X_s}}(u) = \mu^U_{\widetilde{X_s}}(u) \quad (5)$$

$$\upsilon^L_{\widetilde{X_s}}(u) = \upsilon^U_{\widetilde{X_s}}(u) \quad (6)$$

$$\pi^L_{\widetilde{X_s}}(u) = \pi^U_{\widetilde{X_s}}(u) \quad (7)$$

Therefore, based on above Eqs (5)-(7), an interval-valued spherical fuzzy number is as follows:

$$\left(\left[\mu^L_{\widetilde{X_s}}(u), \mu^U_{\widetilde{X_s}}(u) \right], \left[\upsilon^L_{\widetilde{X_s}}(u), \upsilon^U_{\widetilde{X_s}}(u) \right], \left[\pi^L_{\widetilde{X_s}}(u), \pi^U_{\widetilde{X_s}}(u) \right] \right) \quad (8)$$

The Eq (8) can be denoted by $\tilde{\alpha} = ([a,b],[c,d],[e,f])$ in which $a,b,c,d,e,f \in [0,1]$ and $b^2 + d^2 + f^2 \leq 1$. Therefore, $\tilde{\alpha}^* = ([1,1],[0,0],[0,0])$ defined as largest IVSFS, $\alpha^- = ([0,0],[1,1],[0,0])$ is the smallest IVSFS, and $\tilde{\alpha}^{*/-} = ([0,0],[0,0],[1,1])$ represents the median IVSFS number.

Moreover, the union, intersection, and arithmetic operations over IVSFS are defined by (Kutlu Gündoğdu & Kahraman, 2019) as follows:

Definition 1. Let A, B be two IVSFSs then, the union and intersection operations are defined as follows:

$$A \cup B = \begin{Bmatrix} \left[\max\left(\mu_A^L(u), \mu_B^L(u)\right), \max\left(\mu_A^U(u), \mu_B^U(u)\right)\right] \\ \left[\min\left(v_A^L(u), v_B^L(u)\right), \min\left(v_A^U(u), v_B^U(u)\right)\right] \\ \left[\min\left(\pi_A^L(u), \pi_B^L(u)\right), \min\left(\pi_A^U(u), \pi_B^U(u)\right)\right] \end{Bmatrix} \quad (9)$$

$$A \cap B = \begin{Bmatrix} \left[\min\left(\mu_A^L(u), \mu_B^L(u)\right), \min\left(\mu_A^U(u), \mu_B^U(u)\right)\right] \\ \left[\max\left(v_A^L(u), v_B^L(u)\right), \max\left(v_A^U(u), v_B^U(u)\right)\right] \\ \left[\min\left(\pi_A^L(u), \pi_B^L(u)\right), \min\left(\pi_A^U(u), \pi_B^U(u)\right)\right] \end{Bmatrix} \quad (10)$$

Definition 2. Let $\alpha_1 = \{(a_1, b_1), (c_1, d_1), (e_1, f_1)\}$ and $\alpha_2 = \{(a_2, b_2), (c_2, d_2), (e_2, f_2)\}$ are two IVSFS numbers, therefore, arithmetic operations, and the distance between these two numbers are defined as follows:

$$\begin{aligned} \alpha_1 \oplus \alpha_2 = \Big\{ & \left[((a_1)^2 + (a_2)^2 - (a_1)^2(a_2)^2)^{1/2}, ((b_1)^2 + (b_2)^2 \right. \\ & \left. - (b_1)^2(b_2)^2)^{1/2}\right], [c_1c_2, d_1d_2], \Big[\left((1-(a_2)^2)(e_2)^2 + (1-(a_1)^2)(e_2)^2 \right. \\ & \left. - (e_1)^2(e_2)^2\right)^{1/2}, \left((1-(b_2)^2)(f_1)^2 + (1-(b_1)^2)(f_2)^2 - (f_1)^2(f_2)^2\right)^{1/2}\Big]\Big\} \end{aligned} \quad (11)$$

$$\begin{aligned} \alpha_1 \otimes \alpha_2 = \Big\{ & [a_1a_2, b_1b_2], \left[((c_1)^2 + (c_2)^2 - (c_1)^2(c_2)^2)^{1/2}, ((d_1)^2 + (d_2)^2 \right. \\ & \left. - (d_1)^2(d_2)^2)^{1/2}\right], \Big[\left((1-(c_2)^2)(e_1)^2 + (1-(c_1)^2)(e_2)^2 \right. \\ & \left. - (e_1)^2(e_2)^2\right)^{1/2}, \left((1-(d_2)^2)(f_1)^2 + (1-(d_1)^2)(f_2)^2 - (f_1)^2(f_2)^2\right)^{1/2}\Big]\Big\} \end{aligned} \quad (12)$$

$$\begin{aligned} d(\alpha_1\alpha_2) = \tfrac{1}{4}\big(& |a_1^2 - a_2^2| + |b_1^2 - b_2^2| + |c_1^2 - c_2^2| + |d_1^2 - d_2^2| + |e_1^2 - e_2^2| + \\ & |f_1^2 - f_2^2|\big), \end{aligned} \quad (13)$$

Definition 3. It is noticeable that the multiplication and power by a scalar ($\lambda > 0$) can be defined in the following equations.

$$\begin{aligned} \lambda.\tilde{\alpha} = \Big(& \Big[\left(1-(1-a^2)^\lambda,\right)^{1/2}, \left(1-(1-b^2)^\lambda,\right)^{1/2}\Big], [c^\lambda, d^\lambda], \Big[\big((1-a^2)^\lambda - \\ & (1-a^2-e^2)^\lambda\big)^{1/2}, \left((1-b^2)^\lambda - (1-b^2-f^2)^\lambda\right)^{1/2}\Big]\Big) \end{aligned} \quad (14)$$

$$\tilde{\alpha}^{\lambda} = \left(\left[a^{\lambda}, b^{\lambda}\right], \left[\left(1-(1-c^2)^{\lambda},\right)^{1/2}, \left(1-(1-d^2)^{\lambda},\right)^{1/2}\right], \left[\left((1-c^2)^{\lambda} - (1-c^2-e^2)^{\lambda}\right)^{1/2}, \left((1-d^2)^{\lambda} - (1-d^2-f^2)^{\lambda}\right)^{1/2}\right]\right) \tag{15}$$

Furthermore, based on the above definitions, the following relationships for two given IVSFS are established.

- $\tilde{\alpha}_1 \oplus \tilde{\alpha}_2 = \tilde{\alpha}_2 \oplus \tilde{\alpha}_1$ (16)
- $\tilde{\alpha}_1 \otimes \tilde{\alpha}_2 = \tilde{\alpha}_2 \otimes \tilde{\alpha}_1$
- $\lambda.(\tilde{\alpha}_1 \oplus \tilde{\alpha}_2) = \lambda.\tilde{\alpha}_1 \oplus \lambda.\tilde{\alpha}_2$
- $(\tilde{\alpha}_1 \otimes \tilde{\alpha}_2)^{\lambda} = \tilde{\alpha}_1{}^{\lambda} \otimes \tilde{\alpha}_2{}^{\lambda}$
- $\lambda_1.\tilde{\alpha} \oplus \lambda_2.\tilde{\alpha} = (\lambda_1 + \lambda_2)\tilde{\alpha}$
- $\tilde{\alpha}^{\lambda_1} \otimes \tilde{\alpha}^{\lambda_2} = \tilde{\alpha}^{\lambda_1 + \lambda_2}$

3.2. Entropy method

As presented in Figure 1, in this section, we aim to determine the importance or significance of the attributes identified in the previous section for Well Selection. Instead of relying on subjective weighting schemes, we propose combining objective weighting by introducing a new version of the Entropy method with interval-valued spherical fuzzy sets. The steps of this process are presented below.

By setting up the experts' committee, the interval-valued spherical fuzzy entropy-based MCDM method can be described as shown in steps 1 to 8 (Shannon, 2001), being designed to obtain the normalized criteria weight.

Step 1. Obtain the fuzzy decision matrix regarding experts' ideas with triangular fuzzy numbers as defined in the following matrix with *m* alternatives and *n* attributes.

$$x_{ij}^{s} = \begin{bmatrix} x_{11}^{s} & \cdots & x_{1n}^{s} \\ \vdots & \ddots & \vdots \\ x_{m1}^{s} & \cdots & x_{mn}^{s} \end{bmatrix} \tag{17}$$

Step 2. Perform normalization of the decision matrix to find the projection value$\left(p_{ij}^{s}\right)$.

$$p_{ij}^{s} = \frac{x_{ij}^{s}}{\max\limits_{i} x_{ij}^{s}} \; \forall j = 1,2,\dots,n, s \in (B, M, T) \tag{18}$$

Where x_{ij}^{s} represent the interval-valued spherical fuzzy triangular score of alternative i for criterion j, being represented within the bottom: $B = \alpha^{-}$, middle: $M = \tilde{\alpha}^{*/-}$ and Top: $T = \tilde{\alpha}^{*}$ values of the triangular membership function as follows.

$$x_{ij}^{s} = \left(\left[\mu_{\widetilde{x_{ij}^{s}}}^{L}(u), \mu_{\widetilde{x_{ij}^{s}}}^{U}(u)\right], \left[\upsilon_{\widetilde{x_{ij}^{s}}}^{L}(u), \upsilon_{\widetilde{x_{ij}^{s}}}^{U}(u)\right], \left[\pi_{\widetilde{x_{ij}^{s}}}^{L}(u), \pi_{\widetilde{x_{ij}^{s}}}^{U}(u)\right]\right) \tag{19}$$

Step 3. If $p_{ij}^{s} = 0$, then change the value to $p_{ij}^{s} = 1$. This issue is based on the mathematical rule of $\ln(1) = 0$ and $\ln(1) = inf$.

Step 4. Entropy $\left(E_{ij}^{s}\right)$ is a measure of uncertainty expressed by a given probability distribution p_{ij}^{s} and determined for each criterion j by the following equation:

$$En_{j}^{s} = 1 - \frac{2}{5m}\sum_{i=1}^{m}\begin{bmatrix} \left|\left(\mu_{\widetilde{x_{ij}^{s}}}^{L}\right)^{2} - 0.25\right| + \left|\left(\mu_{\widetilde{x_{ij}^{s}}}^{U}\right)^{2} - 0.25\right| \\ + \left|\left(\upsilon_{\widetilde{x_{ij}^{s}}}^{L}\right)^{2} - 0.25\right| + \left|\left(\upsilon_{\widetilde{x_{ij}^{s}}}^{U}\right)^{2} - 0.25\right| \\ + \left|\left(\pi_{\widetilde{x_{ij}^{s}}}^{L}\right)^{2} - 0.25\right| + \left|\left(\pi_{\widetilde{x_{ij}^{s}}}^{U}\right)^{2} - 0.25\right| \end{bmatrix} \tag{20}$$

Step 5. The Dispersion $\left(Dp_{j}^{s}\right)$ of the intrinsic information of each criterion is calculated by the following equation, which indicates how much useful information the relevant index of the $\left(C_{j}\right)$ provides to the decision-maker. The closer the measured values of the index are to each other, the more likely it is that competing alternatives will not differ in terms of that index. Therefore, the role of that indicator in decision-making should be reduced equally

$$Dp_{j}^{s} = 1 - En_{j}^{s}, \forall j \in \{1,2,\dots,n\}, s \in (B, M, T) \tag{21}$$

The measure of Dispersion characterizes the intrinsic contrast intensity of C_{j}. The higher the Dp_{j}^{s}, the more significant the criterion $\left(C_{j}\right)$ will be.

Step 6. Finally the normalized criteria weight$\left(Nw_{j}^{s}\right)$ is presented by Eq. (22):

$$Nw_{j}^{s} = \frac{Dp_{j}^{s}}{\sum_{j=1}^{m} Dp_{j}^{s}}, \forall j \in \{1,2,\dots,n\}, s \in (B, M, T) \tag{22}$$

By obtaining the normalized criteria weight, we enter the third phase of our methodology; rank the alternatives. Thus, by the successive application of IVSFS-ARAS (Zavadskas & Turskis, 2010) (Appendix 1), IVSFS-COPRAS (Zavadskas & Kaklauskas, 1996) (Appendix 2), IVSFS-MOORA (Karande & Chakraborty, 2012) (Appendix 3), and IVSFS-TOPSIS (Deng et al., 2007) (Appendix 4), the target wells' prioritization for HF treatment has been carried out.

The mathematical formulations of four fuzzy MCDM models are presented in appendix A1, A2, A3 and A4.

A: Identify appropriate experts and establish a committee to address this strategic decision problem. This approach helps to avoid bias and minimize partiality in the decision-making process, as involving multiple decision-makers is generally more effective than relying on a single individual.

B: Define the IVSFS scale based on linguistic variables for the entropy, ARAS, MOORA, COPRAS, and TOPSIS methods.

C: Determine the criteria and alternatives based on the experts' analysis of reservoir conditions.

D: Input the criteria into the IVSFS-entropy matrix and assign weights accordingly.

E: Evaluate the performance of each potential well using the IVSFS-ARAS, IVSFS-COPRAS, IVSFS-MOORA, and IVSFS-TOPSIS methods, based on the weighted criteria.

F: Aggregate the results obtained from the MCDM models to establish the final ranking using the Borda method. The Borda method, based on the majority voting rule, is recognized as a consolidation approach. This combination of strategy modeling has also been applied by Akhavan et al. (2015).

G: Perform a sensitivity analysis of all implemented MCDM models to verify the robustness of the results.

The mathematical formulations of the four fuzzy MCDM models are provided in Appendices A1, A2, A3, and A4

4. Case study and the experimental results

4.1. Geological setting of studied wells

Regarding the best candidate well selection for HF treatment, the management team aims to select the best wells from seven available target wells in three Iranian hydrocarbon fields. These three areas are chosen based on the long-term strategic decision of the National Iranian Oil Company (NIOC), which would like to invest in these areas. Based on their evaluation, these three fields have more potential to have a successful operation. Figure 2 illustrates the geographical location of the three fields, which are hatched and labelled in capital letters: A, B and C. Since site C is located at sea, we considered the ‘field type’ (offshore/onshore) attribute in our weighted parameters.

Regarding the selection of the best candidate wells for HF treatment, the management team intends to choose the most suitable wells from seven available target wells located across three Iranian hydrocarbon fields. These three areas have been selected as part of the National Iranian Oil Company's (NIOC) long-term strategic decision to invest in these regions. Based on evaluations, these fields demonstrate higher potential for successful operations. Figure 2 illustrates the geographical locations of the three fields, marked with hatching and labelled in capital letters: A, B, and C. Since Field C is situated offshore, the 'field type' attribute (offshore/onshore) has been included as a weighted parameter in the analysis.

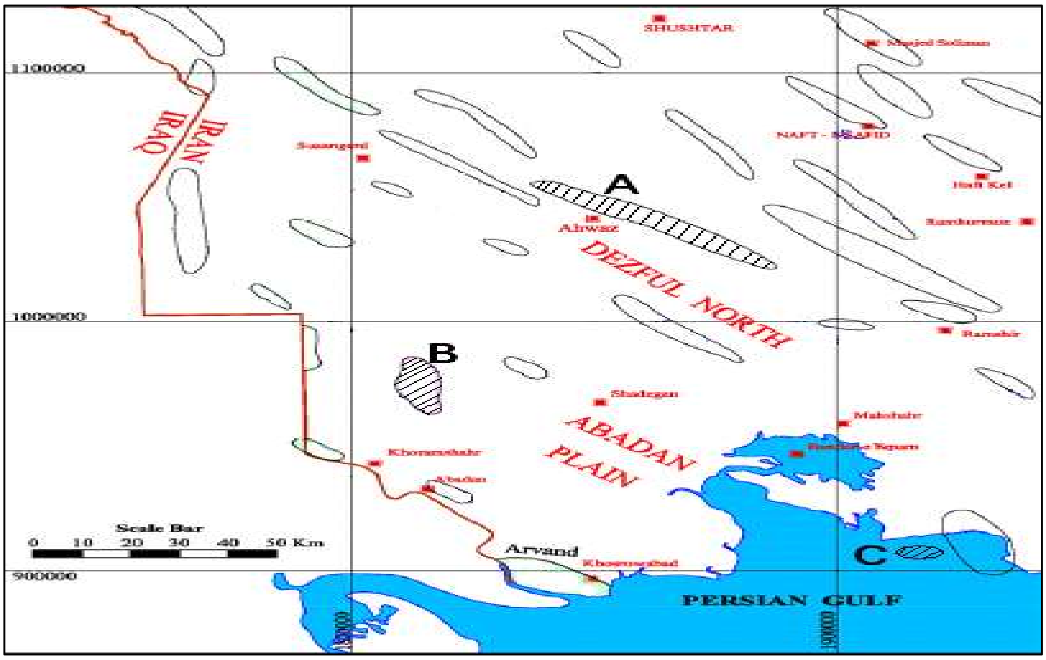

Figure2. The geographical location of three studied Iranian hydrocarbon fields which are hatched and labelled (Iran National Cartographic Center, n.d.)

Field A

Field A is located near the city of Ahwaz, and its structure, similar to most fields in this region, follows the northeast-southwest trend of the Zagros Mountains. The structure is an anticline measuring 75 km in length and 10 km in width at the surface. This field has three reservoir formations, with the Ilam formation being the target for HF treatment. The Ilam formation consists of limestone and dolomite and is the deepest reservoir in Field A. Two wells from this field, Ahwaz (Ilam-zone B), named Az250 and Az268, were selected for candidate analysis and designated as A1 and A2, respectively.

Field B

Field B is located about 30 Km North of Khoramshahr, on the west bank of the Karun River. Its topography is flat, and the ground elevation is about 3-5 meters above sea level. The area is affected by some seasonal flooding. The structure is a symmetrical anticline 24 km long and 10 km wide, elongated in a north-south direction. No significant faults have been highlighted. However, in the 3D seismic interpreted by ENI (an Italian multinational OG company), some fracture trending has been determined (Taheri Nakhost & Shadizadeh, 2013). The target formation in this field is Fahlian, which is dominant; this consists of dolomitic limestone. Regarding data availability, four wells in this field were chosen for candidate investigation (B1, B2, B3, and B4).

Field B is located about 30 km north of Khoramshahr, on the west bank of the Karun River. Its topography is flat, with a ground elevation of approximately 3–5 meters above sea level. The area is subject to seasonal flooding. The structure is a symmetrical anticline measuring 24 km in length and 10 km in width, oriented in a north-south direction. No significant faults have been identified. However, in the 3D seismic data interpreted by ENI (an Italian multinational OG company), some fracture trends have been observed (Taheri Nakhost & Shadizadeh, 2013). The target formation in this field is the Fahlian, a dolomitic limestone formation. Based on data availability, four wells in this field were selected for candidate analysis, designated as B1, B2, B3, and B4.

Field C

Field C is an offshore oil field located in the northwest Persian Gulf. It features an anticlinal structure with a fault on the western flank. The Asmari reservoir, composed of dolomite and limestone, is the target formation for HF treatment. Due to production challenges and data limitations, only one well (C1) was selected from the 12.9 × 6.2 km field in the Asmari formation.

For consistency throughout the paper, we have renamed B1 to B4 as A1 to A4. Additionally, the alternatives within field A (originally A1 and A2) are now designated as A5 and A6, respectively. Finally, C1 has been reassigned as A7

4.2. Calculating the weights of criteria with the IVSFS-entropy method

Our team of decision-makers consists of a group of Iranian specialists in petroleum reservoir engineering and rock mechanics engineering. After defining the goal of the current study, which is candidate well selection for HF treatment; the decision-makers (DMs) introduced fourteen criteria and their sub-parameters that are the most effective parameters related to our goal. These criteria have been defined based on available literature, knowledge, and the experiences of our experts regarding Iranian reservoirs (see Table 1).

Table 2 demonstrates the main information about seven target wells which change to the fuzzy linguistic terms and correspondent fuzzy numbers obtained from Table 3 (Saaty, 2006). In all fields, the upper layer of the target formation is the confining layer, and the fracture cannot be propagated through the upper layer. Also, there is no evidence of sand (or solid) production in target wells.

Table 2. The fuzzy Linguistic variables of seven target wells by experts (Table by Authors)

Criteria	Alternatives						
	A1	A2	A3	A4	A5	A6	A7
C_1	AMI	AMI	AMI	AMI	SMI	SMI	LI
C_2	EI	VHI	EI	SMI	SLI	SLI	LI
C_3	EI	EI	SMI	SMI	SMI	LI	AMI
C_4	VHI	EI	EI	EI	LI	LI	SMI
C_5	EI	EI	EI	EI	SMI	SMI	HI
C_6	LI	LI	ALI	LI	EI	EI	ALI
C_7	VHI	VHI	VHI	EI	AMI	AMI	EI
C_8	SMI	SMI	SMI	HI	SMI	SMI	SMI
C_9	VHI	VHI	VHI	AMI	AMI	AMI	EI
C_{10}	HI	HI	HI	HI	SLI	SLI	EI
C_{11}	VLI	LI	LI	LI	LI	LI	LI
C_{12}	EI	EI	EI	EI	HI	HI	EI
C_{13}	HI	HI	HI	HI	SMI	SMI	EI
C_{14}	HI	HI	HI	HI	SMI	SLI	SMI

In Table 4, the normalized decision matrix (P_{ij}^{s})based on the Eq.(18) is obtained. Then Ln adjustment based on step 3 should be made.

Table 3. Fuzzy linguistic terms and correspondent fuzzy numbers for each criterion and alternative (Table by Authors)

Importance	Correspondent fuzzy numbers
Absolutely more Importance (AMI)	([0.85,0.95], [0.10,0.15], [0.05,0.15])
Very High Importance (VHI)	([0.75,0.85], [0.15,0.20], [0.15,0.20])
High Importance (HI)	([0.65,0.75], [0.20,0.25], [0.20,0.25])
Slightly More Importance (SMI)	([0.55,0.65], [0.25,0.30], [0.25,0.30])
Equally Importance (EI)	([0.50,0.55], [0.45,0.55], [0.30,0.40])
Slightly Low Importance (SLI)	([0.25,0.30], [0.55,0.65], [0.25,0.30])
Low Importance (LI)	([0.20,0.25], [0.65,0.75], [0.20,0.25])

Very Low Importance (VLI)	([0.15,0.20], [0.75,0.85], [0.15,0.20])
Absolutely Low Importance (ALI)	([0.10,0.15], [0.85,0.95], [0.05,0.15])

Table 4. The normalized fuzzy decision matrix of seven alternatives (Table by Authors)

Alternatives	A1						A2						A3						A4						A5						A6						A7					
Criteria	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f
C_1	0.9	1	0.1	0.2	0.1	0.2	0.9	1	0.1	0.2	0.1	0.2	0.9	1	0.1	0.2	0.1	0.2	0.9	1	0.1	0.2	0.1	0.2	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.2	0.25	0.7	0.8	0.2	0.3
C_2	0.5	0.6	0.5	0.6	0.3	0.4	0.8	0.9	0.2	0.2	0.2	0.2	0.5	0.6	0.5	0.6	0.3	0.4	0.6	0.7	0.3	0.3	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.2	0.25	0.7	0.8	0.2	0.3
C_3	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.9	0.95	0.1	0.2	0.1	0.2
C_4	0.8	0.9	0.2	0.2	0.2	0.2	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.6	0.65	0.3	0.3	0.3	0.3
C_5	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.7	0.75	0.2	0.3	0.2	0.3
C_6	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.1	0.2	0.9	1	0.1	0.2	0.2	0.3	0.7	0.8	0.2	0.3	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.1	0.15	0.9	1	0.1	0.2
C_7	0.8	0.9	0.2	0.2	0.2	0.2	0.8	0.9	0.2	0.2	0.2	0.2	0.8	0.9	0.2	0.2	0.2	0.2	0.5	0.6	0.5	0.6	0.3	0.4	0.9	1	0.1	0.2	0.1	0.2	0.9	1	0.1	0.2	0.1	0.2	0.5	0.55	0.5	0.6	0.3	0.4
C_8	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.65	0.3	0.3	0.3	0.3
C_9	0.8	0.9	0.2	0.2	0.2	0.2	0.8	0.9	0.2	0.2	0.2	0.2	0.8	0.9	0.2	0.2	0.2	0.2	0.9	1	0.1	0.2	0.1	0.2	0.9	1	0.1	0.2	0.1	0.2	0.9	1	0.1	0.2	0.1	0.2	0.5	0.55	0.5	0.6	0.3	0.4
C_{10}	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.5	0.55	0.5	0.6	0.3	0.4
C_{11}	0.2	0.2	0.8	0.9	0.2	0.2	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.25	0.7	0.8	0.2	0.3
C_{12}	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.5	0.6	0.5	0.6	0.3	0.4	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.5	0.55	0.5	0.6	0.3	0.4
C_{13}	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.5	0.55	0.5	0.6	0.3	0.4
C_{14}	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.7	0.8	0.2	0.3	0.2	0.3	0.6	0.7	0.3	0.3	0.3	0.3	0.3	0.3	0.6	0.7	0.3	0.3	0.6	0.65	0.3	0.3	0.3	0.3

In the entropy method is applied according to steps 4–6 to determine the criteria weights. Generally, as the number of criteria and alternatives increases, the application of comparison-based models for criteria weighting, such as AHP, becomes more challenging due to inconsistency. This limitation highlights the advantage of the entropy method, which does not require reciprocal comparisons.

Table 5, the entropy method is applied according to steps 4–6 to determine the criteria weights. Generally, as the number of criteria and alternatives increases, the application of comparison-based models for criteria weighting, such as AHP, becomes more challenging due to inconsistency. This limitation highlights the advantage of the entropy method, which does not require reciprocal comparisons.

Table 5. The criteria weight determined by the IVSFS-Entropy method (Table by Authors)

Criteria	En_j^s	Dp_j^s	Nw_j^s
C_1	0.349	0.650	0.104
C_2	0.628	0.371	0.059
C_3	0.605	0.395	0.063
C_4	0.637	0.362	0.057
C_5	0.729	0.270	0.043
C_6	0.498	0.501	0.080
C_7	0.433	0.566	0.090
C_8	0.611	0.388	0.062
C_9	0.338	0.662	0.105
C_{10}	0.579	0.420	0.067
C_{11}	0.466	0.533	0.085
C_{12}	0.738	0.261	0.041
C_{13}	0.579	0.420	0.067
C_{14}	0.549	0.450	0.071

4.3. Evaluation of alternatives and determining the final rank by fuzzy MCDM methods

In this step, we proceed to the second phase of our problem-solving methodology, which involves evaluating the alternatives based on the weights derived from the entropy method and the data provided by experts through the decision matrix. The IVSFS-ARAS, IVSFS-COPRAS, IVSFS-MOORA, and IVSFS-TOPSIS methods are applied in this phase.

IVSFS-ARAS method results: For each criterion in the presented case, the value of the optimality function is determined using IVSFS-ARAS model, then for defuzzification of IVSFS-ARAS, the centre-of-area method is used, and the utility degree of an alternative (k_i) is calculated. The third column of Table 6 represents the crisp value of the optimality function(H_i), the next column contains the utility degree of alternative (k_i), and the rank of an alternative can be found in the last column. A3 and A1 achieve the first and second ranks respectively.

Table 6. The optimality function and degree of alternative value determined by the IVSFS-ARAS method (Table by Authors)

Alternatives	(H_i)						(k_i)	Rank
	a	b	c	d	e	f		
A1	0.175	0.198	0.000	0.000	1.513	0.068	-0.213	2
A2	0.175	0.199	0.000	0.000	0.756	0.069	-0.114	7
A3	0.172	0.196	0.000	0.000	1.517	0.069	-0.214	1
A4	0.173	0.195	0.000	0.000	1.265	0.073	-0.199	6
A5	0.162	0.185	0.000	0.000	1.280	0.074	-0.205	5
A6	0.155	0.176	0.000	0.000	1.284	0.073	-0.209	4
A7	0.126	0.143	0.000	0.000	1.044	0.087	-0.209	3

IVSFS-COPRAS method results: In this method, the relative significance or priority value $(Q_i)$for each alternative is calculated. Finally, the utility degree (N_i) for each alternative is determined, and the complete ranking of partners is obtained (see Table 7).

Table 7 .The relative weight, utility degree, and rank of each alternative determined by the IVSFS-COPRAS (Table by Authors)

Alternatives	P						Q	N	Rank
	a	b	c	d	e	f			
A1	0.997	0.999	3.41E-	2.89E-	0.1	0	-0.503	99%	2
A2	0.996	0.999	2.96E-	0	0.1	0	-0.073	15%	7
A3	0.996	0.999	1.64E-	1.39E-	0.049	0.015	-0.508	100%	1
A4	0.997	0.999	2.63E-	2.39E-	0.049	0.013	-0.333	66%	5
A5	0.995	0.999	2.79E-	2.22E-	0.074	0.017	-0.350	69%	4
A6	1	0.999	7.26E-	5.55E-	0.080	0	-0.358	70%	3
A7	0.978	0.995	0.0001	0.0012	0.027	0.083	-0.238	47%	6

IVSFS-MOORA method results: In this method, the benefits of criteria for each alternative (H_i^s) are calculated, then the defuzzification according to the center-of-area method is applied, and we obtain the ranking of alternatives. A3 and A1 achieve the first and second ranks respectively (Table 8).

Table 8. The benefits of criteria and the rank of each alternative determined by the IVSFS-MOORA (Table by Authors)

Alternatives	A1						A2						A3						A4						A5						A6						A7					
Criteria	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f
$(SOB)_i^s$	0.997	0.999	3.417E-06	2.8927E-05	0.064	0.018	0.996	0.999	2.9616E-06	0	0.063	0.017	0.996	0.999	1.6453E-06	1.3922E-05	0.0495	0.015	0.997	0.999	2.6325E-06	2.3928E-05	0.049	0.013	0.995	0.999	2.793E-06	2.2212E-05	0.074	0.017	0.993	0.999	7.2617E-06	5.5529E-05	0.080	0.022	0.978	0.995	0.0001	0.001	0.027	0.083
$(SONB)$	1.234	0.971	0.003	0.011	0.088	0.181	1.234	0.971	0.003	0.011	0.182	0.181	1.087	0.924	0.015	0.039	0.376	0.299	1.124	0.940	0.006	0.017	0.327	0.262	0.978	0.895	0.010	0.024	0.371	0.326	0.847	0.829	0.022	0.052	0.415	0.398	1.038	0.930	0.006	0.016	0.356	0.243
H_i^s	1.001	0.999	-1.3494E-08	-3.2814E-07	0.059	0.004	1.001	0.999	-1.169E-08	-2.895E-07	0.124	0.004	1.000	0.999	-2.549E-08	-5.501E-07	0.338	0.006	1.000	0.999	-1.733E-08	-4.072E-07	0.279	0.004	0.999	0.999	-2.808E-08	-5.36E-07	0.377	0.008	0.998	0.999	-1.606E-07	-2.903E-06	0.466	0.013	1.001	0.999	-1.346E-06	-2.042E-05	0.334	0.031
H_i^*	-0.503						-0.073						-0.508						-0.333						-0.350						-0.358						-0.238					
Rank	2						7						1						5						4						3						6					

Table 9. The ideal solution, and the rank of each alternative determined by IVSFS-TOPSIS (Table by Authors)

Alternatives	A1	A2	A3	A4	A5	A6	A7
D^+	0.256	0.203	0.201	0.209	0.231	0.228	0.322
D^-	0.182	0.148	0.148	0.141	0.119	0.122	0.205
C	0.416	0.421	0.424	0.403	0.339	0.348	0.388
Rank	3	2	1	4	7	6	5

IVSFS-TOPSIS results: Negative and positive ideal solutions (D^+, D^-) are determined to obtain the ranking score (C) of alternatives. The results of the IVSFS-TOPSIS are shown in Table 9, which indicates that A3 and A2 obtain the first and the second ranks with a C value of 0.424 and 0.421 respectively.

Comparative analysis: To validate the applicability and suitability of the four preferred ranking methods to solve the well selection problem, their ranking performance (see Table 10) is compared using the Borda method. Borda is a known consolidation technique which is based on the majority voting rule. This method is widely applied by different researchers to validate the applicability and suitability of implemented ranking methods (Akhavan et al., 2015).

Table 10. The ranking of alternatives with four methods (Table by Authors)

Alternatives	Method			
	IVSFS-MOORA	IVSFS-TOPSIS	IVSFS-ARAS	IVSFS-COPRAS
A1	2	3	2	2
A2	7	2	7	7
A3	1	1	1	1
A4	5	4	6	5
A5	4	7	5	4
A6	3	6	4	3
A7	6	5	3	6

In this research, the achieved rankings are consolidated using four methods: IVSFS-ARAS, IVSFS-COPRAS, fuzzy IVSFS-TOPSIS, and fuzzy IVSFS-MOORA, as presented in Table 11. For example, well A3 ranks higher than the other wells across the IVSFS-ARAS, IVSFS-COPRAS, fuzzy IVSFS-MOORA, and IVSFS-TOPSIS methods. Therefore, based on majority voting, the rank of well A3 in the table is assigned as 1 when compared to the other wells. We then aggregated the results to determine the final rankings of the alternatives.

Table 11. The Borda method for seven alternatives (Table by Authors)

	A1	A2	A3	A4	A5	A6	A7	Sum	Rank
A1	-----	1	0	1	1	1	1	5	2
A2	0	-----	0	0	0	0	0	0	7
A3	1	1	-----	1	1	1	1	6	1
A4	0	1	0	-----	0	0	1	2	4
A5	0	1	0	1	-----	0	0	2	5
A6	0	1	0	1	0	-----	1	3	3
A7	0	1	0	0	0	1	-----	2	6

To the best of the authors' knowledge, this is the first time that MCDM methods have been applied to the well selection problem. Although the comparison between similar studies is not available, MCDM methods can be evaluated by considering their responses with varying weights via sensitivity analysis.

5. Discussion and sensitivity analysis

The present study utilizes a novel entropy-based fuzzy MCDM approach to identify the optimal candidate for HF treatment in Iranian hydrocarbon reservoirs. The findings indicate that well A3 ranks highest among the evaluated options based on the established criteria. This result aligns with the principles of decision theory, which emphasize the importance of systematic evaluation in complex decision-making scenarios. The proposed stepwise methodology provides a systematic and effective decision-making tool for assessing potential investments in the stimulation of target wells, and it can be readily applied to other carbonate reservoirs beyond the scope of this study. Therefore, our approach offers a practical framework for selecting the most suitable well for HF treatment, contributing to the optimization of reservoir performance and recovery.

In comparing our results with existing literature, we note that previous studies have utilized various MCDM methods, such as the AHP and the TOPSIS, for well selection and evaluation (Mardani et al., 2015). However, these methods often face limitations in handling uncertainty and subjectivity, which our entropy-based fuzzy approach effectively addresses. The incorporation of fuzzy logic enhances the robustness of our rankings by accommodating the inherent uncertainties in the criteria assessments, a factor that has been emphasized in recent research on decision-making in the oil and gas sector (Gul & Ak, 2021).

Our analysis of raw data from fourteen criteria reveals a strong correlation between ranking outcomes and calculated weights. Well A3 emerges as the top candidate for HF treatment, demonstrating high levels of positive criteria and moderate values for negative criteria. In contrast, well A7, characterized by a high water cut and medium to high economic and financial risks, ranks the lowest. These findings offer valuable insights for selecting the most promising candidate wells and contribute to the broader discourse on effective resource management in hydrocarbon extraction.

The process of ranking alternatives is closely intertwined with the distribution of weights assigned to each criterion. As highlighted in the literature, sensitivity analysis is crucial for understanding the stability of decision-making results and assessing how variations in criteria weights affect the final alternative ranking (Mulliner et al., 2016). To conduct a sensitivity analysis, we varied the criteria weights and monitored the resulting changes in the ranking of alternatives across different MCDM methods. The findings of this analysis, presented in Figure 3, illustrate the significant impact of changes in criteria weights on the final ranking of alternatives. This aligns with existing theories on decision-making, which suggest that even minor adjustments in criteria weights can lead to substantial shifts in rankings, thereby emphasizing the need for careful consideration of weight assignments in MCDM applications.

Sensitivity Analysis of Criteria Weights Across Varying Weight Levels

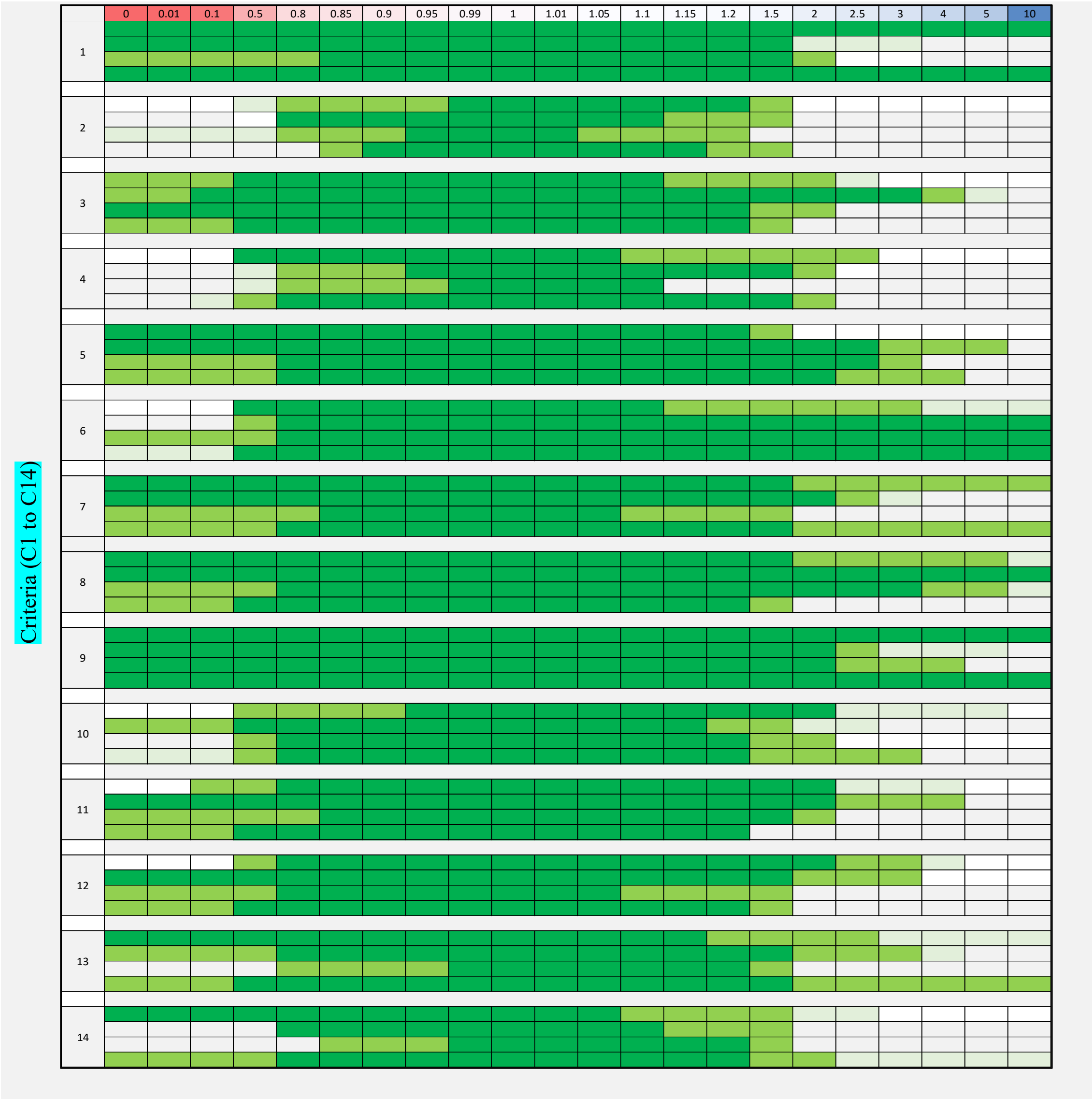

Figure 3. Criteria sensitivity to change (criteria are numbered on the left side and vertical strip line stands for the sensitivity of criteria) (Figure by Authors)

Dark green lines illustrate the acceptable variation of criteria weight when the ranking does not change, whereas the light green lines represent one change in the priority of alternatives. In principle, vertical strip line stands for the sensitivity of criteria to the change; wherein shorter stripes show higher sensitivity levels. Decision-making criteria are numbered on the left side of the chart in the following order: 1. Field type, 2. Water cut, 3. Collaborative Logistics, 4. Regulatory Pressure, 5. Operational parameters, 6. Economic and financial risks, 7. Well direction, 8. Environment and Sustainability, 9. Well completion method, 10. Political stability, 11. Sand production, 12. Production method, 13. Reservoir pressure (psi), and 14. Resource Risks. For each criterion, the first line is the implementation results of IVSFS-COPRAS; following with IVSFS-ARAS, IVSFS-TOPSIS, and IVSFS-MOORA (bottom).

As shown in Figure 3, It is evident that 'well completion method,' 'field type,' 'environment and sustainability,' and 'economic and financial risks' have the least influence on the final ranking of alternatives. In contrast, 'water cut,' 'regulatory pressure,' 'production method,' and 'resource risks' have a moderate impact on the final ranking of alternatives. Furthermore, the IVSFS-TOPSIS method exhibits the highest sensitivity to changes in weight. Additionally, the ranking of alternatives is more sensitive when the criteria weights exceed 1, compared to when they are below 1.

One sensitivity coefficient reported here is the sensitivity of criterion *i,* represented as SC_i which is calculated based on the relative number of changes that occurred in the ranking orders (displayed in Figure 3) and according to Eqs. (23) and (24), wherein D_{ij} corresponds the relative number of changes made in the ranking order with regard to i^{th} criteria and the j^{th} MCDM method.

$$D_{ij} = \sum_{n=1}^{j} \frac{d_{ij}}{\sum d_{ij}} , i = 1, \ldots ,14; j = 1, \ldots ,4 \tag{23}$$

$$SC_i = \frac{\sum_{n=1}^{i} D_{ij}}{\sum_{n=1}^{i} \sum_{n=1}^{j} D_{ij}}, i = 1, \ldots ,14; j = 1, \ldots ,4 \tag{24}$$

Figure 4 presents the value of SC_i for the candidate well selection problem.

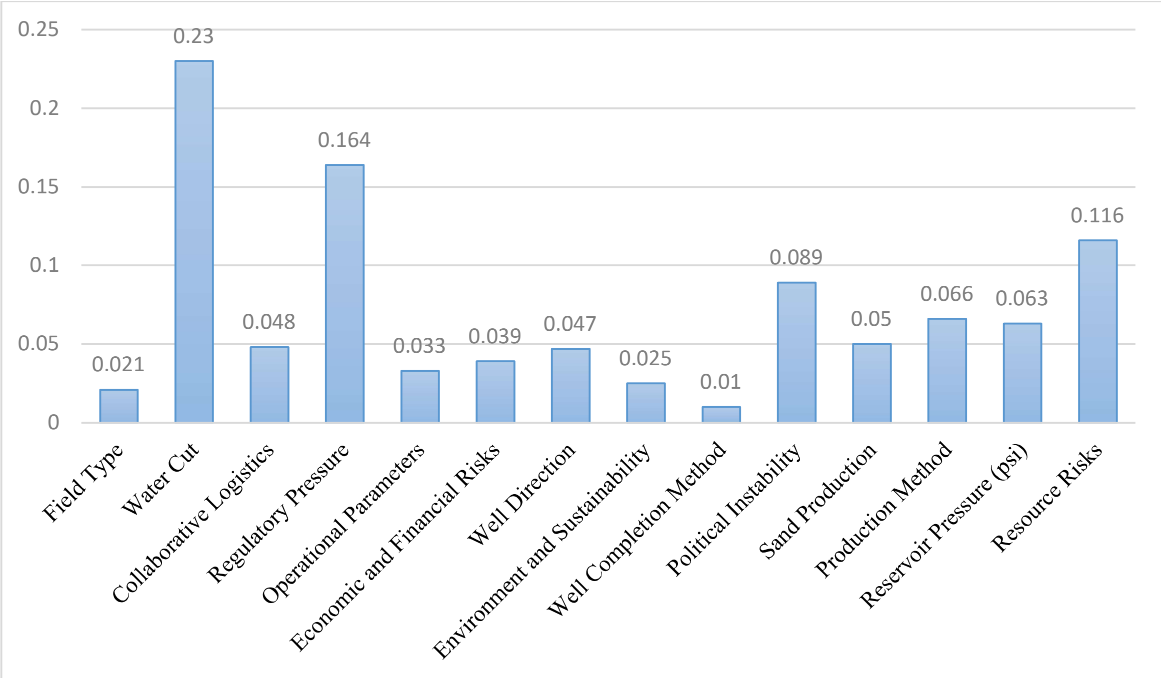

Figure 4. Relative sensitivity to the changes in ranking regarding criteria (Figure by Authors)

According to Figure 4, it is obvious that the alternatives' rankings are more sensitive to 'water cut', 'regulatory pressure', and 'resource risks. Conversely, 'well completion method', 'field type' and 'environment and sustainability' have fewer relative influences on changes occurred in the subsequent ranking.

In addition to SC_i, another sensitivity coefficient is considered, i.e., SC_j which is associated with the relative sensitivity of ranking achieved by j^{th} MCDM method to D_{ij}. SC_j is obtained by Eq. (25).

$$SC_j = \frac{\sum_{n=1}^{j} D_{ij}}{\sum_{n=1}^{j} \sum_{n=1}^{j} D_{ij}}, i = 1, \dots, 14; j = 1, \dots, 4 \tag{25}$$

Table 12 contains the value of SC_j with regard to criterion *i*. In Table 12, each cell represents the sensitivity coefficient of the associated MCDM method to the corresponding criteria in which higher values introduce more sensitivity of the MCDM method to the variation of criteria weights.

Table 12. Comparison of ranking sensitivity to different criteria weights within MCDM methods (Table by Authors)

Criteria/Method	IVSFS-COPRAS	IVSFS-ARAS	IVSFS-TOPSIS	IVSFS-MOORA
Field type	0.000	0.039	0.042	0.000
Water Cut	0.238	0.179	0.190	0.330
Collaborative Logistics	0.076	0.021	0.027	0.073
Regulatory Pressure	0.128	0.276	0.161	0.088
Operational Parameters	0.046	0.013	0.028	0.045
Economic and financial risks	0.080	0.039	0.013	0.020
Well Direction	0.018	0.029	0.091	0.044
Environment and Sustainability	0.019	0.000	0.019	0.069
Well Completion Method	0.000	0.023	0.015	0.000
Damage Penetration (skin)	0.142	0.095	0.050	0.069
Sand Production	0.057	0.021	0.042	0.084
Production Method	0.063	0.034	0.084	0.082
Reservoir Pressure (psi)	0.042	0.052	0.113	0.034
resource risks	0.092	0.179	0.125	0.061

The sensitivity of MCDM methods to variations in the 'water cut' parameter is apparent. Consequently, these methods demonstrate lower sensitivity to factors such as the 'well completion method' and 'environment and sustainability.' The distinct sensitivity patterns exhibited by each MCDM method can be identified through pairwise correlation analysis of the rankings they produce. The analysis reveals that the highest sensitivity correlation occurs between IVSFS-MOORA and IVSFS-COPRAS, followed by IVSFS-TOPSIS and IVSFS-ARAS. Conversely, the lowest sensitivity correlation is observed between IVSFS-MOORA and IVSFS-ARAS. Figure 5 illustrates which method is the most robust in response to variations in criteria weights.

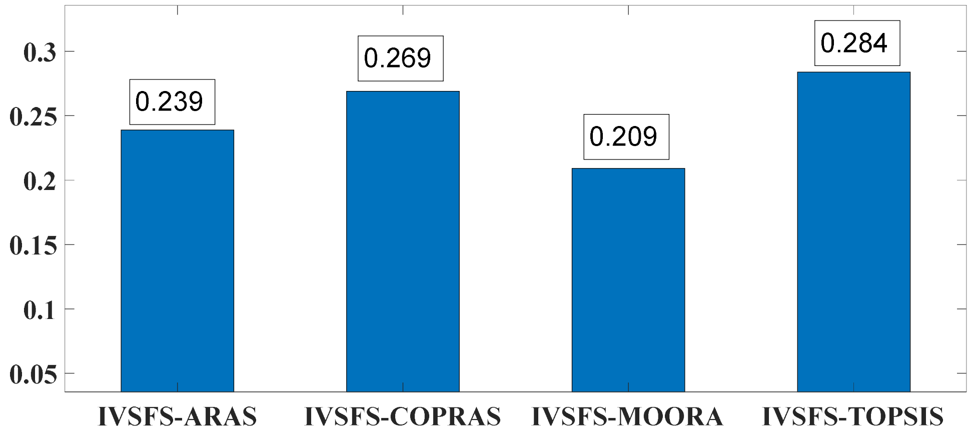

Figure 5. Relative sensitivity to change in ranking with regard to methods (Figure by Authors)

Figure 5 reflects the relative close matching among the MCDM methods. It could be suggested that the IVSFS-MOORA and IVSFS-ARAS methods could be noted as less sensitive to criteria weight changes and are thus more robust methods.

Understanding the significance and ranking of each alternative in the final selection of wells for this project is crucial. This process involves identifying the alternative that ranks highest based on the seven most critical criteria: C1, C6, C7, C9, C11, C13, and C14. Furthermore, conducting a sensitivity analysis of the well alternatives can reveal potential changes in the final rankings if certain criteria are excluded. This analysis excludes consideration of each key criterion's influence at every stage. Ultimately, it ensures that the decision-making process remains robust and adaptable to variations in criteria importance.

Since we have focused solely on the most important criteria from a managerial perspective, it is crucial to demonstrate how these criteria influence the final ranking of the alternatives. To illustrate this, we have deliberately excluded these criteria from our calculations to observe the resulting rankings of the alternatives in their absence. Figure 6 illustrates the ranking outcomes of the alternatives when these key criteria are omitted.

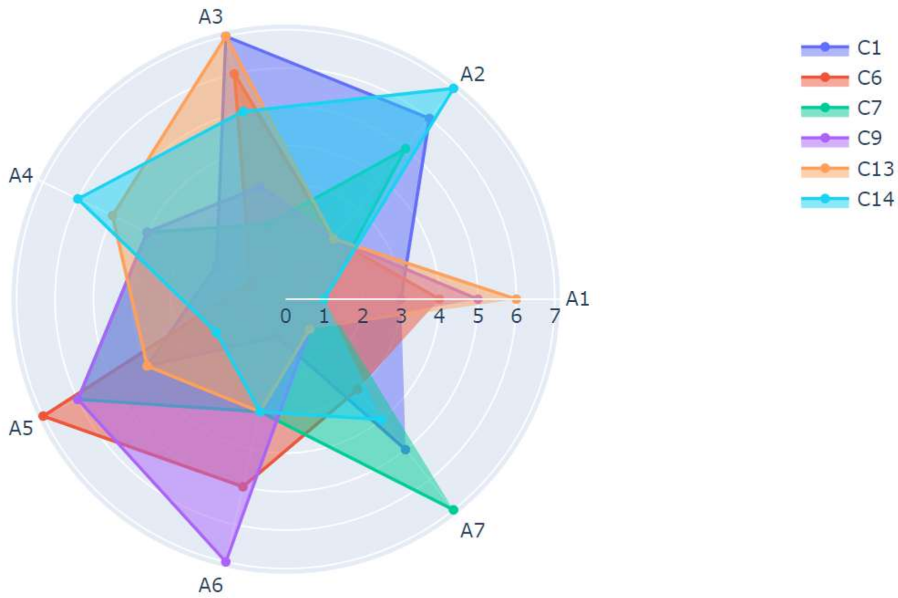

Figure 6. Sensitivity analysis of alternatives ranks with "only" impact of the criteria (Figure by Authors)

When Criterion C1, related to water cut, is excluded, A6 consistently emerges as the top contender, underscoring its stable performance across various metrics. In contrast, A7's performance is notably impacted, suggesting its ranking benefits significantly from low water cut values. This observation indicates that, even with the water cut factor removed, A6 remains a formidable option due to its inherent qualities, such as reservoir characteristics or operational efficiency.

In scenario C6, the exclusion of well direction significantly diminishes A5's standing, underscoring its reliance on this factor for a favorable evaluation. In contrast, A4 demonstrates improved performance, suggesting that it is less dependent on well direction and may provide a more adaptable approach to well selection.

In scenario C7, when environmental and sustainability criteria are excluded, A7 ranks the lowest, indicating that its strong initial ranking was heavily influenced by its environmental performance. This change suggests that A7's strategy should not rely solely on its sustainability attributes, especially if these factors are deprioritized.

In the case of C9, where political stability is disregarded, A7's rank declines significantly, implying that it derives considerable benefit from its stable regional context. Meanwhile, A1 appears more appealing, suggesting that political considerations previously overshadowed its potential. In environments where political risk is minimized, A1 may emerge as a stronger option.

When C11 is excluded and the production method is not considered, A3's ranking drops markedly, confirming the critical importance of its specialized production techniques. Meanwhile, A6 rises in rank, indicating that its prior lower position was influenced by less optimal production methods. A3 remains a prime candidate when its specialized production is a priority, while A6 could be preferable in scenarios where variability in production methods is acceptable.

The analysis concerning C13 reveals that A7 benefits most from the exclusion of resource risk factors, as it had been previously penalized for higher risks. Conversely, A3's ranking deteriorates, suggesting that its previously inflated position was due to lower perceived risks. This underscores the need for a robust reassessment of risk management strategies, particularly for A7, while A3 may need to address potential underestimations of its risk exposure.

Lastly, omitting C14, which focuses on the field type, leads to a significant decline in A2's rank, highlighting its reliance on favorable field conditions. In contrast, A1 shows an improved ranking, indicating resilience against varying field conditions. This resilience makes A1 a strong candidate in scenarios with uncertain field-type advantages, whereas A2 may require more careful evaluation under such circumstances.

The analysis indicates that some oil wells, such as A7, achieve high rankings when certain criteria are included, but their rankings decline when these criteria are excluded. This highlights a strong dependency on specific positive factors, such as sustainability and political stability. Conversely, wells like A6 exhibit consistent performance across various criteria, indicating a more balanced profile.

The managerial strategy should therefore be multifaceted: it should take into account the inherent core strengths of each well while avoiding over-reliance on a single criterion.

Furthermore, to better understand the impact of each criterion, we examine a scenario where the manager chooses to focus exclusively on the most important criteria. This analysis explores the potential changes in the final rankings of the alternatives under such conditions. To illustrate this, Figure 7 presents the rankings derived when the manager considers only one of these important criteria at a time.

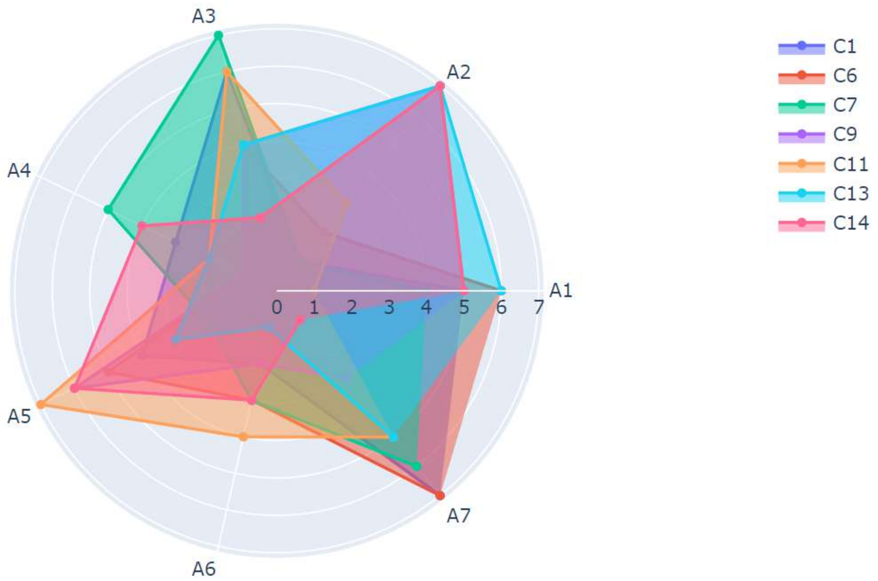

Figure 7. Sensitivity analysis of alternatives ranks with “without” impact of the criteria (Figure by Authors)

By considering C1, A2 emerges as the top contender when focusing exclusively on water cut, a factor typically viewed as negative. This suggests that A2 offers the most favorable water-cut conditions among all alternatives—an advantage that should not be overlooked. Conversely, A7 is the least favorable under this criterion, indicating a greater need for extensive water-handling infrastructure, which could significantly impact overall costs and environmental strategy. For projects where minimizing water production is vital, A2 should be prioritized, presenting a promising solution.

Focusing on C6, it becomes evident that well direction significantly impacts accessibility and extraction efficiency. A4 ranks the highest in this criterion, demonstrating optimal alignment with the reservoir, which is a potential advantage. In contrast, A7 ranks the lowest, suggesting challenges related to the reservoir's orientation—an issue that should be approached with caution. A4 should be considered for projects where well direction is critical to maximizing recovery. For A7, additional interventions or technologies may be required to mitigate its directional disadvantages, presenting a potential hurdle.

Concentrating on C7 (Environment and Sustainability) reveals that A2 tops the rankings under this criterion, indicating a leadership position in environmental considerations—an advantage with significant potential. A3, on the other hand, ranks the lowest, which may reflect less favorable sustainability practices. For projects prioritizing environmental impact, A2 offers benefits such as lower regulatory hurdles and enhanced community relations. Conversely, A3 might face more environmental challenges or regulatory scrutiny, a potential drawback to consider.

A4 and A7 exhibit the most substantial and least favorable advantages, respectively, when political stability is the sole focus. This suggests that A4 operates in a significantly stable political environment, while A7 does not. For geopolitically sensitive projects, A4 represents a lower-risk profile. However, in the case of A7, comprehensive risk mitigation strategies should be implemented to address political instability effectively.

A1 is the most favored when evaluated based on the production method, indicating that its approach is highly effective. In contrast, the lowest ranking for A5 suggests that its production method may be less suited to the specific reservoir conditions. A1 likely offers the highest operational efficiency, which is critical for meeting production targets and minimizing costs. A5, however, may require methodological adaptations to achieve comparable efficiency levels.

Focusing on C13 highlights that A6 leads the rankings, implying the lowest perceived resource risks. Conversely, A2 and A7 exhibit the highest resource risks. Managers should prioritize A6 in projects where minimizing resource-related uncertainties is paramount. For wells like A2 and A7, thorough due diligence and a robust focus on risk assessment will be essential.

When examining C14, A1 and A7 score the highest and lowest, respectively. This indicates that A1 benefits from a more advantageous field type, while A7 might encounter operational complexities or cost issues related to its field type. Selecting A1 could yield benefits due to favorable field conditions, such as logistical convenience or lower costs. For A7, careful consideration is necessary to determine whether the benefits outweigh the challenges associated with its field type.

By individually analyzing key criteria, it becomes evident that certain oil wells exhibit specific strengths and weaknesses depending on the criterion in question. For instance, A2 and A4 demonstrate resilience in environmental sustainability and political stability, respectively—factors critical for long-term operational success. Conversely, A7 frequently ranks lower across multiple criteria, identifying it as a well that may pose significant challenges and require additional investment to mitigate its disadvantages

6. Theoretical, managerial, and policy implications

This study brings meaningful insights to theory, management, and policy in how we make decisions under pressure and uncertainty especially when choosing sites for hydraulic fracturing (HF) in oil and gas. On the theory side, it sharpens how fuzzy logic can work within MCDM methods. By using an entropy-based method to weigh different factors, the study better captures the gray areas in expert opinions. It also shows how shifts in those weights can significantly change how choices are ranked, giving depth to how we think about decision theory. The introduction of the IVSFS-MCDM framework adds something new to the field. It builds on tools like AHP and TOPSIS, but goes further—allowing decision-makers to handle uncertainty and conflicting inputs with more flexibility and realism. For managers, this framework is a practical asset. It helps guide smarter, more data-informed choices on where to invest, weighing not just what's profitable, but also what's environmentally and technically sound. It includes tools for sensitivity analysis, helping companies foresee potential risks and plan accordingly. Plus, it's built to work across different regions and project types, making it ideal for global or complex operations. At a policy level, the work emphasizes the need to factor sustainability into early project decisions. It supports using clear, measurable tools like entropy weighting, to reduce bias and build trust in the decision process. It also encourages teamwork across disciplines and highlights the importance of investing in research to support better decision tools like IVSFS-MCDM. In the end, this study doesn't just push technical boundaries, it offers a grounded approach for those making hard decisions in a high-stakes industry.

7. Conclusion

This study proposes a novel IVSFS-entropy MCDM method for selecting optimal candidate wells for hydraulic fracturing in oil and gas fields, aligning with project management principles within an academic context. The method employs a Borda approach to integrate four MCDM methods, providing a weight assignment for each criterion and resulting in a final ranking of target wells. A comprehensive sensitivity analysis confirms the robustness of the method, emphasizing the equal importance of managerial and engineering factors in the selection process, thereby reflecting the interdisciplinary approach encouraged in project management academia.

The implementation of the proposed procedure in geological exploration has the potential to streamline reservoir engineering processes and enhance project management outcomes in the sector. Unlike traditional hydraulic fracturing methods that rely solely on mathematical approaches, the proposed model emphasizes professional expertise, aligning with the academic project management principle of integrating expert judgment. The incorporation of the fuzzy entropy method considers the influence of various economic attributes in the oilfield selection process, echoing the project management focus on comprehensive risk and economic assessment, ultimately leading to more precise and accurate results. Overall, this approach provides a nuanced and robust framework for reservoir characterization and selection, offering valuable insights for both academic research and practical project management in the oil and gas industry.

The study's findings designate alternative A3 as the optimal candidate, followed by others in a specific order, which are pivotal for integrating academic project management methodologies with practical engineering applications. These findings highlight the significant factors that impact the hydraulic fracturing treatment problem, reinforcing key project management concepts such as risk assessment and resource management.

In this context, the absence of a specific well chosen and stimulated based on the outcomes underscores a gap between academic theory and practical application—a common challenge in project management research. Nevertheless, the proposed approach presents a potentially viable alternative to, or supportive tool for, the costly numerical simulation process involved in well selection. This suggests a valuable intersection between academic research and practical project management.

To enhance the rigor and comprehensiveness of this study while aligning with academic project management standards, a numerical simulation of hydraulic fracturing in target wells could be conducted. This would evaluate the efficacy of the proposed methodology and bridge the gap between theory and practice, a core aim of project management academia. Further validation of the methodology through comparisons with actual well candidate selection outcomes could strengthen the connection between academic research and industry application.

The sensitivity analysis results provide valuable lessons and implications for the oil industry, particularly in improving business operations. Understanding how each well's performance would behave in the presence or absence of specific criteria allows for the identification of attributes that make wells robust under varying conditions. These insights can be used to categorize wells based on specific criteria, enhancing resource allocation to wells with consistently strong performance across multiple factors. The results increase efficiency in various processes and operations, requiring fewer resources to achieve desired outcomes. This analysis informs decisions on selecting wells that meet current and future designs, ensuring operational improvements based on performance-driven criteria.

The policy implications of the results underscore the need for dynamic regulations in the oil industry. Policy frameworks that prioritize criteria such as environmental conservation and political stability encourage eco-conscious business practices while ensuring optimal project management outcomes. Such policies drive the development of advanced technologies aimed at achieving corporate sustainability goals. Policies based on these findings would not only support the transition to the green energy sector but also enhance the effectiveness of project management criteria by favoring practices aligned with environmental sustainability. A policy aligned with these criteria paves the way for improved efficiency and sustainability in the system.

Additionally, employing other fuzzy MCDM models and expanding the study to include grey or interval-based MCDM models could deepen academic investigation into project management methodologies, fostering a broader understanding of the proposed approach and its applications in the oil and gas industry.

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