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ORIGINAL ARTICLE

Risk Assessment of Water Structure Projects Using Fuzzy Multi-Attribute Decision-Making Methods: Fuzzy OWA and Fuzzy SAW (Case Study: S1 Wellhead Platform in the Salman Oil Field)

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Abstract

Civil engineering projects, including the construction of oil platforms, are inherently associated with various types of risks from different perspectives. Risk management in large-scale water and marine structure projects, such as the construction of oil platforms, is essential due to the multiple uncertainties and extensive environmental and human factors involved. Identifying, assessing, and prioritizing risks are critical steps in managing these projects effectively. This study aims to identify and rank key risks in the construction of an oil platform using fuzzy multi-attribute decision-making models. In this research, risks in the areas of engineering, execution, passive defense, and the environment were identified through a literature review and expert consultation using brainstorming techniques. Subsequently, a risk management team identified 21 key risks and established 8 evaluation criteria through focused group discussions. To achieve the research objectives, two questionnaires were developed. The first questionnaire was used to form a pairwise comparison matrix and determine the weights of the criteria using the Fuzzy Buckley method, while the second questionnaire assessed the importance of the risks. The collected data were analyzed using the Fuzzy Simple Additive Weighting (SAW) and Ordered Weighted Averaging (OWA) methods. The results indicated that the primary risks were related to the execution phase, highlighting the need for special attention to these risks to improve project outcomes. Unlike many traditional methods, the fuzzy OWA method effectively incorporates the subjective characteristics, risk appetite, and risk aversion of decision-makers, proving to be efficient in risk evaluation.

Keywords: FOWA, Fuzzy SAW, MADM method, Risk of marine structures, Salman oil field.

1. Introduction

The identification and prediction of risks in the construction of water and marine structures, such as offshore oil platforms, are crucial for preventing adverse incidents. In the construction process of an oil platform, factors such as technical complexities, extensive resource requirements, uncertainties, and the socio-political consequences of project failures hold significant importance. Due to these challenges, risk management in such projects is of paramount importance (Mianji et al., 2022). Risk management encompasses a set of processes aimed at identifying, analyzing, and responding to risks in projects to maximize positive outcomes and minimize the negative impacts of unforeseen events. This process serves as a systematic and proactive approach to project control and uncertainty reduction, spanning all stages of a project, from planning to execution and monitoring. It must be continuously iterated to ensure its effectiveness (Tabejamaat et al., 2024). Risk identification is vital not only during the planning phase but also throughout project execution, especially when changes occur, or new issues arise. Each stage of the risk management process must be thoroughly and accurately conducted to facilitate improvements in subsequent stages (Chapman and Ward, 2003). In this study, the first step involves identifying the key risks associated with the construction of the S1 wellhead platform in the Salman oil field. Subsequently, the identified risks will be prioritized based on their significance using expert opinions and multiple criteria, applying fuzzy multi-criteria decision-making models such as Fuzzy SAW and Fuzzy OWA.

Multi-criteria decision-making (MCDM) models, particularly fuzzy models, have been widely employed as powerful tools for evaluating and prioritizing risks in various projects. Fuzzy models excel in handling uncertainties and capturing the subjective judgments of decision-makers, making them especially suitable for environments characterized by incomplete information and high uncertainty.

Numerous studies have highlighted the effectiveness of fuzzy decision-making methods in addressing complex risk assessment challenges. These models enable a nuanced evaluation by incorporating linguistic variables and membership functions, which help in reflecting the inherent vagueness and imprecision in expert judgments. Numerous studies have addressed risk analysis in various environments. Some notable research in this field includes: Dahab et al. (1994) identified and ranked key environmental risks in groundwater, analyzing the risk of nitrogen contamination using fuzzy decision-making models. Sadiq (2003) assessed and managed risks associated with the discharge of drilling waste into the sea (Sadiq, 2003). Their study demonstrates that preventive actions and proper management of these waste materials can help mitigate negative impacts on marine ecosystems.

Pohekar and Ramachandran (2004) examined the application of various multi-criteria decision-making methods in sustainable energy planning. Their study shows that these methods can assist in selecting optimal strategies for managing sustainable energy resources. Levy (2005) utilized multicriteria decision-making models and decision support systems for flood risk assessment and management. The study emphasizes the importance of advanced decision-making tools in identifying and reducing flood risks.

The authors present various decision-making approaches, including network analysis models, and evaluate multiple criteria such as economic, social, and environmental factors for flood crisis management. This approach aids in making more informed decisions to address flood threats and minimize the resulting damages.

Kentel and Aral (2007) explored the use of fuzzy multi-objective decision-making methods in groundwater resource management. Their research employs fuzzy decision-making models to address issues related to water allocation and optimal management of groundwater resources under conditions of uncertainty. Hansson et al. (2011) investigated financial risk management in natural disasters. The study emphasizes the importance of multi-criteria decision-making models for analyzing disaster management policies and presents a framework that includes simulation modeling, decision-analytic tools, and proposed policy strategies for handling natural disasters.

This approach helps decision-makers choose optimal strategies in complex situations with significant uncertainties, particularly in environmental and societal risk management. Hansson et al. (2013) proposes a framework for applying Multiple Criteria Decision Making (MCDM) in flood risk management. The framework includes a flood simulation model, a decision-making tool, and suggested policy strategies, incorporating environmental and social factors in the evaluations. Using the Bac Hung Hai polder in northern Vietnam as a case study, the research demonstrates the importance of adding a multi-criteria perspective to flood management decisions and involving stakeholders in consequence analysis and criterion weight determination.

Andrić and Lu (2016) focused on the risk assessment of bridges during their operational lifecycle under the influence of various hazards. Their study combined risk assessment techniques and decision-making models to identify and prioritize different hazards that may affect bridge safety and performance. Dehdasht et al. (2017) assessed risks in oil and gas construction projects using a combination of fuzzy decision-making models, specifically DEMATEL and ANP.

This integrated approach helps project managers develop more effective risk management strategies by identifying and understanding the relationships among different risks. Tian et al. (2018) presented a multi-criteria risk assessment model for safety risks in the oil and gas industry, emphasizing the importance of considering different expert perspectives to improve the accuracy and reliability of risk management models. Khakzad (2020) applied the OWA method with varying levels of ORness to select the best sediment management methods. The study demonstrated how OWA could be used to weight the importance of different criteria based on decision-maker preferences, improving decision-making processes in environmental and natural resource management.

Djenadic et al. (2022) introduced a novel risk assessment model combining fuzzy logic and multi-criteria decision-making (MCDM) to better manage uncertainties associated with risk. This model is particularly useful for complex projects, such as construction and oil and gas projects, as it helps analyze non-linear relationships between risks and supports optimal decision-making. Ayoubi Ayoublu et al. (2022) investigated flood risk assessment using MCDM models and data mining techniques, identifying and ranking flood risk factors for a region in Shiraz. Their findings suggest that this combined approach can help identify high-risk areas and develop effective risk management strategies.

Tsakalerou et al. (2022) utilized multi-criteria decision-making analysis to evaluate the impacts of offshore construction projects. Their research developed intelligent decision-making models specifically for assessing the risks and impacts associated with offshore platform construction.

Ali et al. (2024) assessed and ranked risks associated with rig installation operations in oilfield environments. Using fuzzy multi-criteria decision-making models, their study addressed the uncertainties in risk assessment and provided recommendations for improving safety and reducing risks during these operations. These studies highlight that fuzzy multi-criteria decision-making models are highly effective tools for evaluating and managing risks in complex and high-risk projects, such as offshore and oilfield construction projects. Despite the strengths of the aforementioned studies, there are certain gaps that still need to be addressed. Many existing models fail to adequately handle complex uncertainties, particularly those related to human judgment and behavioral aspects. Additionally, most research focuses on single decision-making methods without integrating various approaches that could enhance the accuracy and reliability of risk assessments.

Furthermore, the interactions between risks are often not comprehensively analyzed, and environmental and social contexts specific to individual projects are frequently overlooked. In this study, to bridge some of these gaps, a model is proposed that not only integrates multiple decision-making methods but also combines complex uncertainty management and considers project-specific factors, thereby improving the robustness and relevance of risk evaluations in dynamic and uncertain environments.

In this study, fuzzy SAW and OWA models are employed to rank risks in the offshore oil platform construction project. These models are utilized to evaluate the importance of risks based on various criteria selected by experts. By integrating these decision-making techniques, the study aims to provide a comprehensive and nuanced risk assessment that accounts for both the complexity and uncertainty inherent in such large-scale projects.

2. Materials and Methods

2.1. Methodology

Based on previous research, oil and gas industry projects are characterized by high levels of complexity and uncertainty, making investments in such projects inherently risky (Mellers and Chang, 1994). Therefore, identifying risks and optimizing their management are crucial for the success of these projects. The goal of risk management is to increase the likelihood and impact of positive events while reducing the likelihood and impact of negative events on projects (Stulz, 2008). Effective risk management relies on detailed planning, which includes methodology, roles and responsibilities, budgeting, scheduling, risk categorization, and definitions of risk impacts and probabilities (Hopkin, 2018).

The objective of this study is to identify the risks associated with a project and then prioritize and rank them using multi-criteria decision-making (MCDM) methods.

The central question addressed in this research is to identify which risks have the most significant impact on the project. From this perspective, the initial identification of risks is considered the most critical step in risk management. Establishing a risk management team at the project's inception can facilitate and enhance the quality of the risk identification and analysis process. Throughout the project, maintaining a collaborative effort among the risk management team—comprising project managers, experts, stakeholders, and risk management specialists—can greatly aid in the processes of risk assessment, monitoring, and control.

In this study, a model is proposed in which key risks in the offshore oil platform construction project are identified based on expert opinions and then prioritized using MCDM methods. To evaluate the efficiency of the proposed model, data related to the S1 wellhead platform in the Salman Oil Field, located south of Lavan Island in the Persian Gulf, are utilized. The steps of the proposed model are presented in the following sections. Fig.1. shows a picture of the S1 wellhead platform in the Salman Oil Field.

Fig. 1. The S1 wellhead platform in the Salman Oil Field

2.1.1. ISO 31000 standard

In this study, the ISO 31000 standard is utilized for managing the risks associated with the offshore oil platform construction project. According to this standard, the risk management process comprises five key steps:

1. Establishing the Context**:** This step involves defining objectives, determining the scope and criteria, and identifying stakeholders, which helps in gaining a better understanding of the organization’s conditions and environment.
2. Risk Identification: At this stage, potential risks that could impact the objectives are identified.
3. Risk Assessment: This step includes analyzing and evaluating the likelihood and impact of risks to prioritize them.
4. Risk Treatment**:** In this phase, necessary actions are planned and implemented to reduce, eliminate, or accept risks.
5. Monitoring and Review**:** This step involves continuous tracking of risks and the effectiveness of risk management actions. It also ensures that the risk management process remains updated and aligned with organizational and environmental changes (Kloman, 2010)

The present article focuses on the first three steps of this standard. Fig. 2. shows the risk management process in the ISO 31000 standard.

2.1.2. Data collection

This study relies on a library research method. Initially, primary information required for establishing the theoretical framework is collected and compiled by consulting specialized books, journals, and credible scientific websites. Subsequently, the data necessary to test the research hypotheses are gathered through questionnaires. Two expert-designed questionnaires are utilized in this research. The first questionnaire is developed for pairwise comparisons of the criteria, while the second one is designed to rate each option against each criterion. Both questionnaires are distributed to experts for their input.

Fig. 2. The risk management process in the ISO 31000 standard

2.2. Identification and selection of key risks

In multi-criteria decision-making, various options are prioritized based on weighted criteria. The first step in identifying and prioritizing risks is forming a risk management team. In the second step, the team must identify initial risks with the aim of addressing various aspects of the project. In this study, initial risks across different domains were identified through a review of previous research, foundational studies, and the application of brainstorming. Brainstorming is a structured approach to generating new ideas and solutions by freely expressing initial thoughts in a group setting (Osborn, 1953).

Subsequently, key risks were selected using the Focus Groups technique. Focus Groups is a qualitative method where a small group of individuals, guided by a facilitator, engage in discussions on a specific topic to explore their perspectives and experiences in depth. Focus groups were first mentioned in the literature prior to World War II, and later disseminated by Robert K. Merton in 1956 as an alternative to individual interviews (Côté-Arsenault, 2013). This method enables researchers to gather unique insights into individuals' attitudes, beliefs, and behaviors.

2.3. Determination of criteria

The prioritization of key risks in this study is conducted using multi-attribute decision-making (MADM) models based on a set of defined criteria. A review of previous studies indicates that risk evaluation criteria are often distilled into a few fundamental attributes that encompass various aspects of risk. In this research, the selection of criteria is carried out through the application of the Focus Groups technique.

2.3.1. Weighting the attributes

The importance of all attributes is not necessarily equal. Therefore, in the decision-making process, the relative weight of each attribute must be calculated. Weighting in multi-attribute decision-making (MADM) is the process of assigning a relative importance to each attribute based on its significance in the decision-making context (Wind and Saaty, 1980). In this study, the weighting of attributes in terms of their significance has been conducted using the Buckley model.

2.4. Risk evaluation and ranking

In the proposed model, risk evaluation and ranking are performed using multi-attribute decision-making (MADM) methods. Decision-making involves clearly defining objectives, identifying possible alternatives, evaluating their feasibility, assessing the consequences of implementing each alternative, and finally selecting and implementing the optimal choice.

The quality of management fundamentally depends on the quality of decision-making, as the effectiveness and efficiency of strategies and the quality of outcomes derived from them all hinge on the quality of the decisions made by the manager. In most cases, decision-making is deemed satisfactory when the process considers multiple criteria.

These criteria can be either quantitative or qualitative. Multi-criteria decision-making (MCDM) methods, which have garnered significant attention in recent decades, utilize multiple criteria for optimality assessment instead of relying on a single criterion. MADM, a subset of MCDM, focuses on evaluating alternatives based on several attributes.

2.5. Methods used in the proposed model

This study employs brainstorming for the initial identification of risks and focus groups to determine evaluation criteria and identify key risks. Additionally, the fuzzy Buckley method is applied for attribute weighting, while fuzzy SAW and fuzzy OWA methods are used for risk prioritization. These methods are briefly introduced in this section.

2.5.1. Brainstorming method

Brainstorming is a group technique used for generating ideas and solving problems. This method is often employed in the early stages of problem-solving or strategy development and helps teams think more creatively. The main advantages of brainstorming are fostering creativity and enhancing collaboration, while a major disadvantage is the potential generation of irrelevant or weak ideas. The steps in the brainstorming method include: setting the objective, gathering the group, generating ideas, withholding initial evaluation during the session, creating and combining ideas, and finally, evaluating the ideas.

The use of brainstorming encourages a broad scope of ideas and creativity. The goal of idea generation in this method is to maximize the quantity of ideas, not their quality. For this reason, in this study, brainstorming was employed in the initial identification of risks to ensure the inclusion of various potential risks and to consider the different aspects of the project.

2.5.2. Focus groups method

Focus groups are a qualitative data collection technique used to gather participants' perspectives, opinions, and ideas on a specific topic. In this method, a group of individuals participates in a session led by a facilitator or moderator. The purpose of these sessions is to engage in free discussions, exchange ideas, and collect in-depth information from diverse viewpoints (Krueger, 2014). The ability for participants to exchange opinions and uncover unexpected perspectives is one of the main benefits of this method.

The steps for conducting a focus group are: setting the objective, selecting participants, appointing a moderator or facilitator, holding the session, recording the data, and analyzing the data. The use of focus groups helps deepen the discussions and enhances the quality of the analyses. In selecting the final criteria and determining key risks, the quality and depth of the data are crucial. For this reason, the focus group method was used in these two stages.

2.5.3. Fuzzy Buckley method

The Buckley method is a multi-criteria decision-making technique used to analyze and evaluate pairwise comparisons in situations where the data may be uncertain or ambiguous (Buckley, 1985). The Fuzzy Buckley Method is a multi-criterion decision-making (MADM) model that utilizes the Fuzzy Analytic Hierarchy Process (FAHP) approach. This method is particularly useful in situations where data and evaluations involve uncertainty and ambiguity. In this study, since the questionnaire data are associated with uncertainty, the Fuzzy Buckley Trapezoidal Method is applied to assign weights to the criteria.

After collecting expert opinions through Questionnaire 1 and forming the pairwise comparison matrix, the fuzzification of this matrix is performed using the trapezoidal scale. where the scale is based on a standardized range of linguistic values. These values, which correspond to levels of importance or preference, are utilized to capture the uncertainty of expert judgments. The use of the trapezoidal fuzzy scale allows for a more flexible representation of the decision-makers' evaluations. Subsequently, the geometric mean of each row is calculated (Eq.1).

$$\tilde{z_i} = \left(\prod_{j=1}^{n} \tilde{t_{ij}}\right)^{\frac{1}{n}} \quad (1)$$

where i and j represent the rows and columns of the pairwise comparison matrix, $\tilde{t_{ij}}$ is the fuzzy trapezoidal number, and $\tilde{z_{ij}}$ is the Buckley geometric mean. Then, the geometric means of the rows are normalized (Eq.2).

$$\tilde{w_i} = \frac{\tilde{z_i}}{\sum_{i=1}^{n} \tilde{z_i}} \quad (2)$$

where $\tilde{z_{ij}}$ is the Buckley geometric mean, and $\tilde{w_i}$ is the normalized fuzzy weight for index i, representing the relative importance of this index compared to other indices. After calculating the geometric mean and normalizing, the final fuzzy weight for each index is obtained. These weights represent the relative importance of each index in an environment with uncertainty and are used as inputs in subsequent stages of the analysis.

2.5.4. Fuzzy SAW decision-making method

The Simple Additive Weighting (SAW) method is one of the oldest techniques in MADM within the realm of classical mathematics. In this study, the fuzzy SAW decision-making method is applied in the fuzzy mathematics domain, using the trapezoidal fuzzy weights derived from the Buckley method for weighting the indices. To reduce the uncertainty in questionnaire data, trapezoidal fuzzy numbers are employed in this method. The computational steps are outlined as follows.

2.5.4.1. Normalization of Fuzzy values for each index

To compare the fuzzy values of options for each index, normalization of fuzzy values is performed. Since all indices in this study are considered positive, for each index (c_j), which is represented as a trapezoidal fuzzy number (Eq(3)), normalization (Eq(4)) is carried out and denoted as r_{ij}.

$$c_j = (l_{ij}, m_{ij}, n_{ij}, u_{ij}) \quad (3)$$

$$r_{ij} = \left(\frac{l_{ij}}{u_j}, \frac{m_{ij}}{u_j}, \frac{n_{ij}}{u_j}, \frac{u_{ij}}{u_j}\right) \quad (4)$$

where u_j is equal to the maximum u_{ij} across all alternatives.

2.5.4.2. Calculation of the Fuzzy SAW score for each alternative

After normalization, the fuzzy score S_i for each alternative is obtained as the weighted sum of the attributes (Eq. 5):

$$S_i = \sum_{j=1}^{n} W_j * r_{ij} \quad (5)$$

where W_j is the fuzzy weight for attribute j, previously calculated using the trapezoidal fuzzy Buckley method, and r_{ij} represents the normalized fuzzy values for alternative i and attribute j.

2.5.4.3. Fuzzy multiplication calculation

To calculate the fuzzy multiplication between weights and fuzzy values, trapezoidal fuzzy multiplication is used. If the fuzzy weight W_j (Eq. 6) and the normalized fuzzy value r_{ij} (Eq. 7) are given, the fuzzy multiplication is performed for each attribute j and each option i (Eq. 8).

$$W_j = (p_j, q_j, r_j, s_j) \quad (6)$$
$$r_{ij} = (l_{ij}, m_{ij}, n_{ij}, u_{ij}) \quad (7)$$
$$r_{ij} * W_j = (p_j.l_{ij}, q_j.m_{ij}, r_j.n_{ij}, s_j.u_{ij}) \quad (8)$$

2.5.4.4. Defuzzification

The final result of fuzzy SAW is a fuzzy number. To use this value in decision-making, it must be converted into a crisp value. This process is known as defuzzification. One of the common methods for defuzzification is the use of the centroid method. The centroid formula for a trapezoidal fuzzy number xix_ixi (Eq. 9)) is as follows (Eq. 10).

$$x_i = (a_i, b_i, c_i, d_i) \quad (9)$$
$$C = \frac{a + 2b + 2c + d}{6} \quad (10)$$

(In this formula, C represents the centroid).

2.5.5. Fuzzy OWA decision-making method

In a decision-making problem, risk-tolerant individuals emphasize the positive attributes of an option, while risk-averse individuals focus on its negative attributes and base their selection criteria on them. The Ordered Weighted Averaging (OWA) method is capable of calculating the degree of risk-aversion and risk-tolerance of individuals and incorporating it into the final option selection. This method was proposed by (Yager, 1988). In fuzzy OWA, the principles of fuzzy logic are used to quantify and aggregate information. The steps of the fuzzy OWA method are as follows:

2.5.5.1. Defining Fuzzy inputs

In the fuzzy OWA method, input values are defined as fuzzy sets. X is a set of input values (Eq. 11), where each x_i is a triangular or trapezoidal fuzzy number.

$$X = \{x1, x2, \ldots, xn\} \quad (11)$$

2.5.5.2. Sorting Fuzzy input values

Similar to classical OWA, the fuzzy input values x_i must be sorted in descending order. Sorting fuzzy values requires a comparison criterion. One common criterion for comparing fuzzy numbers is the use of the median or central value of the fuzzy number. If X is the set of fuzzy input values, the sorted fuzzy set will arrange the fuzzy values of X in descending order.

2.5.5.3. Defining Fuzzy weights

The OWA weights are defined as fuzzy values. If W is the set of fuzzy weights, each w_i is a fuzzy number (Eq. 12). The fuzzy weights are also defined as triangular or trapezoidal fuzzy sets.

$$W = \{w1, w2, \ldots, wn\} \quad (12)$$

An important condition in fuzzy OWA is that the sum of the fuzzy weights must equal 1 (Eq. 13). This sum is also calculated fuzzily, and this condition must be satisfied when determining the weights.

$$\sum_{i=1}^{n} W_i = 1 \quad (13)$$

2.5.5.4. Calculating the final result of Fuzzy OWA

The final result of fuzzy OWA is calculated by combining the sorted fuzzy values and the fuzzy weights. In the general fuzzy OWA formula (Eq. 14),y_i represents the sorted fuzzy values, and W_i represents the fuzzy weights corresponding to each value y_i.

$$OWA_{fuzzy} = \sum_{i=1}^{n} W_i * y_i \quad (14)$$

In this formula, the fuzzy multiplication between the weights and the fuzzy values is denoted by the symbol (*). The calculation of the fuzzy multiplication between trapezoidal fuzzy numbers and the defuzzification of the outputs of this method is similar to the fuzzy SAW method. In this way, the final fuzzy number is converted into a crisp value, which can then be used for the final decision-making.

3. Results and Discussion

3.1. Formation of the risk management team

Based on the first step of the ISO 31000 standard, which is Establishing the Context, the risk management team for the construction of the S1 Wellhead Platform in the Salman Oil Field was formed. This team consists of 15 specialized members. The team includes the project manager as the team leader, the planning officer, the safety officer, the client representative, the coordinating force, and specialists in the fields of legal, financial, environmental, civil defense, crisis management, operations and maintenance, and engineering (including marine structures, water, electrical, and mechanical engineering).

In this regard, the risk management team conducted brainstorming sessions with the majority of members present, inviting 25 experienced engineers and workers involved in the construction or maintenance of similar projects, as well as 20 students from related fields of study. These sessions were held to identify and prioritize risks and various ideas by leveraging the practical and academic experiences of the participants.

The members of the specialized focus group sessions were the same as those in the risk management team. Each specialist in the risk management team also organized separate meetings with their advisors at their discretion to gain more precise analyses of the existing risks and facilitate the decision-making process.

3.2. Introduction of indicators

By reviewing previous studies, in the first step, 11 indicators were selected as the initial indicators. Due to the overlap of some of the initial indicators, the risk management team, using the Focus Group technique, determined 8 indicators for assessing the main risks of the S1 Wellhead Platform project in the Salman Oil Field. The project manager, as the team leader of risk management, acted as the observer or facilitator in the Focus Group method. The evaluation indicators in this study are: risk frequency, risk occurrence severity, risk detectability, risk occurrence probability, impact on quality, impact on time, impact on cost, and impact on scope. To weight the indicators, Questionnaire No. 1 was designed. This questionnaire evaluates the importance of each indicator relative to the others through pairwise comparisons.

The questions in this questionnaire are structured using a standardized fuzzy scale with linguistic values ranging from "Very Low" to "Very High." These values are used to represent the importance of each indicator based on expert judgment. The results from this questionnaire were then used to determine the fuzzy weights of the indicators.

These indicators were weighted based on the output data of Questionnaire No. 1, using the fuzzy AHP method, and the results are presented in Table.1.

Table 1. Fuzzy Weights of the Indicators Using the Buckley Method

Indicator	Fuzzy Weight of the Indicator
Risk Frequency	(0.434, 0.552, 0.592, 0.714)
Occurrence Intensity	(0.648, 0.762, 0.۸02, 0.929)
Detection Capability	(0.241, 0.356, 0.396, 0.524)
Occurrence Probability	(0.573, 0.692, 0.732, 0.867)
Impact on Quality	(0.167, 0.282, 0.322, 0.388)
Impact on Time	(0.182, 0.259, 0.339, 0.425)
Impact on Cost	(0.193, 0.268, 0.348, 0.438)
Impact on Scope	(0.151, 0.194, 0.214, 0.294)

The weighting of the indicators shown in Table 1 is only used in the fuzzy SAW decision-making model. The fuzzy OWA method, as explained earlier, operates based on the concept of ordinal weights. To reduce the uncertainty of the questionnaire data, trapezoidal fuzzy numbers are used in the fuzzy Buckley method, and a standardized fuzzy scale is applied to quantify the expert opinions.

3.3. Risk identification

The risks identified in this research, based on previous studies and the brainstorming method, amount to 59 cases, including areas of execution, engineering, environmental, and civil defense. Of these, 21 risks were ultimately selected as the most important and key risks by the risk management team based on the focus group method. These risks serve as alternatives in the decision-making models used in this study. Although the brainstorming method focuses on individuals' creativity and generating a wide range of ideas, recording weak or relatively irrelevant ideas is a natural outcome of this approach.

Accordingly, in this study, the brainstorming method was used in the initial risk identification stage, while the focus group method was applied in the key risk determination stage. In the process of selecting these risks from the 59 initial risks, the prior knowledge and collaboration of experts played a fundamental role due to the application of the focus group technique. Some of the initial risks overlapped conceptually; several of these risks were merged, and the rest were eliminated. Based on their experience and prior knowledge, and through an analysis of the project’s context, the experts identified and removed irrelevant or less significant risks from the list.

Finally, some risks were deemed negligible in the present case study based on their likelihood or severity and were disregarded. This process of selecting key risks helped simplify and facilitate the subsequent stages of risk analysis and decision-making.

3.4. Risk prioritization (Ranking)

Questionnaire number two was designed to prioritize the risks by determining the importance of each risk for each indicator. Finally, based on the output data from the questionnaires, the risks were prioritized using two methods: fuzzy SAW and fuzzy OWA. To reduce the uncertainty of the questionnaire data, trapezoidal fuzzy numbers were used in both the fuzzy SAW and fuzzy OWA methods. The ranking of the risks, as the outputs of these two methods, is shown in Table 2.

Fig. 3. displays the overall risk ranking results using the fuzzy SAW method and three fuzzy OWA states (Risk-Seeking, Risk-Neutral, and Risk-Averse) in four different conditions as a column chart.

Also Fig. 4. the results show accurate risk ranking for four risk categories (engineering, implementation, environment, and safety and civil defense) using fuzzy SAW and fuzzy OWA methods in four different conditions as a column chart.

Table 2. Risk Ranking using Fuzzy SAW and Fuzzy OWA Methods

Risks	SAW	OWA (Risk-Seeking)	OWA (Neutral)	OWA (Risk-Averse)
Engineering Risks				
1. Increase in dredging volume due to errors in hydrographic studies	18	15	12	12
2. Human error in calculations	11	12	11	11
3. Uncertainties in calculations	15	19	18	20
Execution Risks				
4. Error in installation of platform components (deck and platform)	12	13	10	13
5. Transportation errors (onshore – offshore)	6	8	3	11
6. Fatigue of components due to repeated loading and unloading	14	17	17	17
7. Work stoppage due to lack of necessary materials and equipment, including sanctions	1	1	1	2
8. Work stoppage due to interference from the operation and use of other platforms	7	9	8	9
9. Negative impact of adverse weather conditions on execution	4	3	2	1
10. Work stoppage due to delays in obtaining permits	13	8	13	11
Safety and Civil Defense Risks				
11. Impact of enemy threats (military and cyber-attacks, etc.)	8	4	5	4
12. Impact of natural threats (landslides, earthquakes, waves, and winds)	2	5	3	7
13. Lack of access to support bases and crisis management	3	9	6	2
14. Failure to consider the political, economic, and social consequences of project failure	5	7	4	5
15. Fire and explosion	10	14	10	1
Environmental Risks				
16. Seizure and destruction of the natural ecosystem	17	16	14	10
17. Air pollution caused by incomplete combustion and flare shutdown	19	15	16	20
18. Marine water pollution caused by oil spills and leaks	9	6	7	6
19. Disposal of sanitary waste into the sea	16	19	21	14
20. Corrosion of platform foundation in tidal zones due to the growth of marine plants and bacteria	21	20	18	16
21. Soil pollution	20	21	19	21

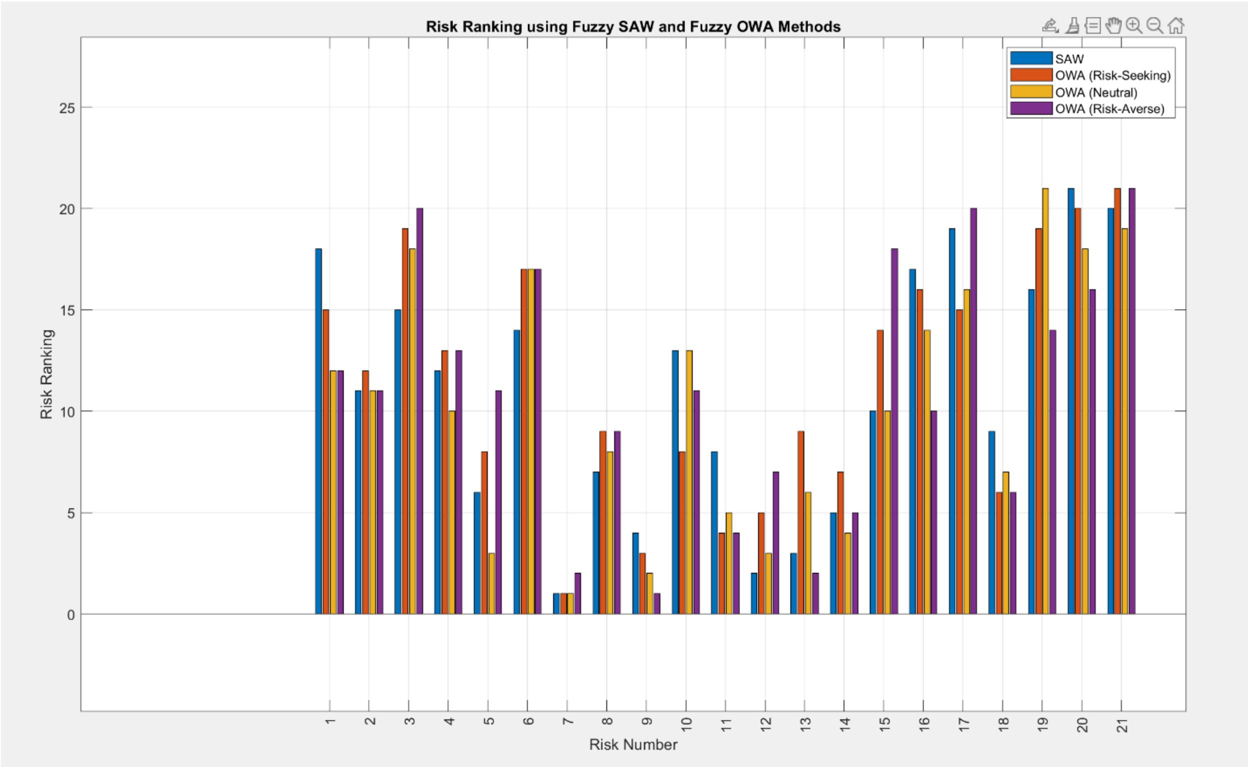

Fig. 3. Overall risk ranking results using the fuzzy SAW method and three fuzzy OWA states (Risk-Seeking, Risk-Neutral, and Risk-Averse) in four different conditions.

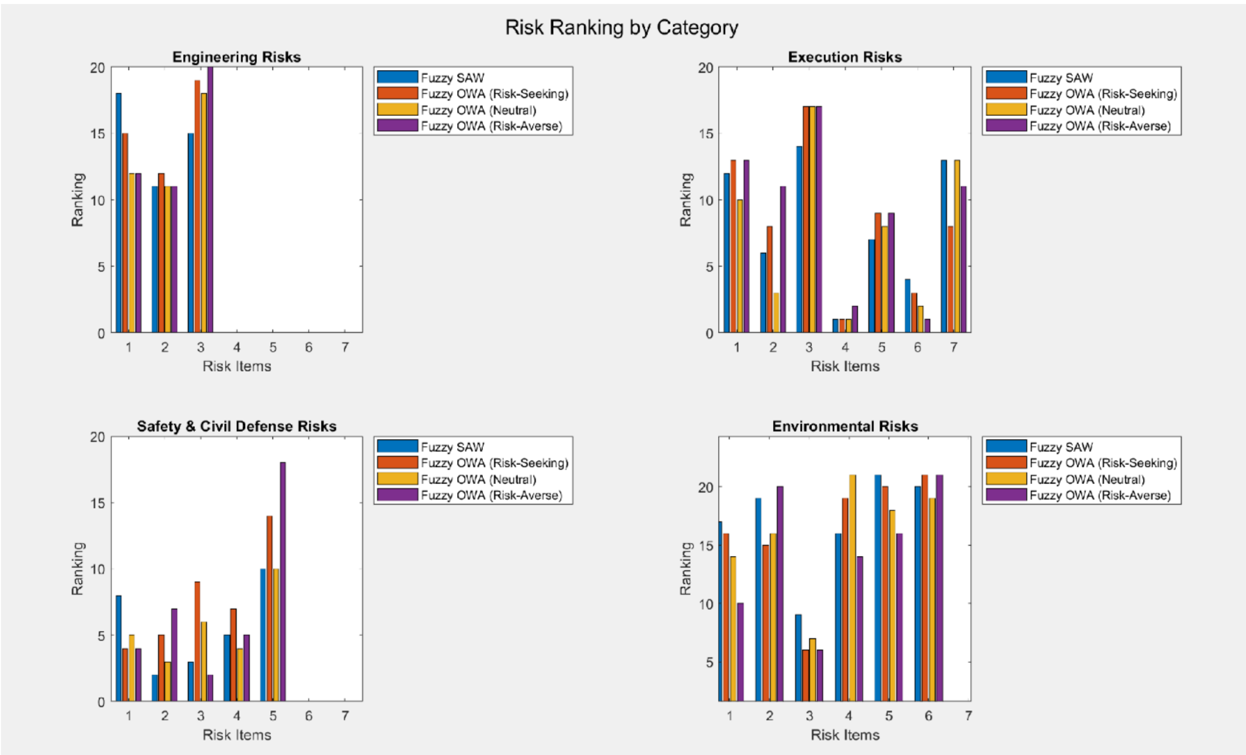

Fig. 4. Detailed risk ranking results for four risk categories (Engineering, Execution, Environmental, and Safety & Civil Defense) using the fuzzy SAW and fuzzy OWA methods

4. Discussion

In this study, the significant risks of the S1 wellhead platform project in the Salman oil field were identified, assessed, and prioritized. Initially, the primary risks in the engineering, operational, environmental, and safety and civil defense areas were determined based on the opinions of experts and specialists. Then, using fuzzy multi-criteria decision-making methods, namely SAW and OWA, and based on eight criteria, the risks were prioritized. The results obtained from comparing these methods and the findings of this study are as follows:

4.1. Ranking results from the methods

The analysis of the ranking results from both the SAW and OWA methods (risk-seeking, neutral, and risk-averse scenarios) indicates that the majority of risks are related to operational and civil defense risks. Therefore, addressing these risks (and other risks based on the prioritization of each method) can play a significant role in guiding the project planning. Giving special attention to these risks at all stages of the project will maximize positive outcomes and minimize the likelihood of negative results.

4.2. Vulnerability and conservatism of decision-makers

The results of the study show that risk-taking and conservatism of decision-makers influence the identification of risk management priorities. In situations where risk management principles are not properly implemented, depending on the level of conservatism of the managers, some important risks may be overlooked or excessively emphasized.

4.3. Key risks of the project

This study revealed that the most significant risks of the S1 wellhead platform construction project include: the risk of operational stoppage due to shortages of materials and equipment caused by sanctions, the risk of the effects of natural threats such as landslides, earthquakes, waves, and wind, the risk of lack of access to support bases and crisis management, and the risk of negative weather conditions affecting project execution.

4.4. Comparison with previous studies

A comparison conducted by Mianabadi and Afshar in 2008 between the TOPSIS and OWA methods in a classical mathematical environment showed that TOPSIS is a risk-averse method, and its results are closer to the risk-averse results of the OWA method (Mianabadi et al., 2011). In this study, however, using fuzzy SAW and various fuzzy OWA scenarios, it was observed that the results obtained from SAW are closer to the risk-seeking OWA in some risks, and in others, they align more with the risk-averse or neutral scenarios. Studies such as Khakzad (2020) and Tsakalou et al. (2022) have demonstrated the effectiveness of MCDM models in prioritizing risks in offshore projects. Similarly, the findings of the present study reinforce the applicability of fuzzy MCDM methods for evaluating complex risks while highlighting the need to adapt these methods based on decision-makers' preferences.

The emphasis on environmental and social factors in previous research (e.g., Levy, 2005; Hanson et al., 2011) aligns with the approach of the present study, which incorporates such factors into the evaluation criteria. Unlike studies that focus on a single MCDM method (e.g., Poh and Ramachandran, 2004; Tian et al., 2018), this research demonstrates the advantages of combining SAW and OWA to address both objective and subjective aspects of risk assessment.

The integration of expert-driven criteria and the use of focused group discussions during risk identification in this study address the gap noted in previous research regarding the lack of comprehensive stakeholder engagement. By explicitly evaluating decision-makers' subjective preferences, such as risk aversion levels in OWA, this study introduces a novel framework for adaptive risk management in dynamic environments.

4.5. Determining the best method

Decision science does not aim to uncover absolute truths or find final answers; rather, it is a scientific effort to make rational decisions. None of the decision-making methods have an absolute superiority over the others, and in certain specific cases, each method may have relative advantages. In risk management, the level of risk tolerance of decision-makers can influence the results of risk prioritization and ranking.

4.6. Comparison of used methods

The primary reason for selecting the SAW method in this study was its simplicity and widespread applicability in identifying project risks. The SAW method is well-known for its straightforward calculations, which make it a common choice in various decision-making scenarios. However, as noted earlier, one limitation of SAW is its inability to consider the subjective characteristics of decision-makers, providing uniform solutions regardless of whether the decision-maker is risk-seeking or risk-averse. To address this limitation, the OWA method was employed, offering distinct advantages. OWA can account for the subjective characteristics of decision-makers by considering their preferences and attitudes toward risk. Its ability to model trade-offs among attributes, rank operator values before multiplying by the weight vector, and use linguistic quantities for determining weights makes it a more suitable option for risk management in this context.

This feature is particularly significant when prioritizing risks in complex and large-scale projects, such as marine oil platform construction. Additionally, the use of fuzzy models in both SAW and OWA methods was aimed at reducing uncertainties inherent in risk assessment processes. By incorporating fuzzy logic, these methods provide flexibility in handling linguistic and imprecise data, which is a common characteristic of real-world risk assessment scenarios. This integration not only enhances the robustness of the decision-making process but also ensures that the selected methods are well-suited for addressing the complexities and uncertainties of marine project risks.

5. Conclusion

The fuzzy SAW and OWA methods were employed in this study as effective tools for project risk management, particularly in large-scale and complex projects such as oil platforms. These methods help project managers identify and evaluate risks systematically while enabling them to make more informed decisions in the face of uncertainty. The fuzzy SAW method provides simplicity and clarity, making it a suitable choice for projects where a straightforward aggregation of attributes is required. On the other hand, the OWA method's ability to integrate linguistic values and prioritize risks based on the subjective characteristics of decision-makers makes it particularly advantageous. By applying these methods, project managers can effectively address the uncertainties inherent in marine structure construction projects, design robust strategies to mitigate risks, and reduce their adverse effects across all project stages.

Considering the importance of risk management in water and marine structure projects, future research could focus on improving the accuracy and validity of existing fuzzy models, combining empirical data with advanced simulations to achieve more precise results in risk evaluation. Additionally, examining the subjective characteristics of decision-makers in different water and marine project conditions could help identify risk tolerance and aversion more accurately and lead to the development of more effective strategies for risk reduction. On the other hand, by utilizing modern data analysis methods such as machine learning and data mining, future studies can provide more accurate predictions and simulations regarding risks and their consequences in water and marine projects, which will enhance decision-making accuracy and efficiency compared to current conventional methods. Furthermore, future research could combine various decision-making methods to create more comprehensive and flexible models, thereby helping to identify risks more accurately in water and marine projects.

Ultimately, the practical application of these models in marine platform construction projects, dam building, and other water-related projects, especially under specific regional and climatic conditions, could demonstrate the practical impacts of these methods in reducing risks and improving managerial decision-making. This paper focuses on the first three standard steps of ISO31000: determining the context, identifying risks, and evaluating them. Addressing risk responses and continuous monitoring and surveillance, as important subsequent steps of ISO31000, could serve as motivation for future research.

Future research could consider conducting sensitivity analysis to investigate how changes in the weights of the criteria might affect the rankings of risks. This would help in better understanding the robustness of the model and how variations in decision-makers' preferences could influence risk prioritization. Such an analysis can enhance the reliability and adaptability of fuzzy decision-making models in dynamic environments.

6. Disclosure statement

No potential conflict of interest was reported by the authors.

7. References

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