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An Enhanced Failure Mode and Effects Analysis Risk Identification Method Based on Uncertainty and Fuzziness

Longting Wang[1], Yanqun Yu[1*], Zimo Liu[2], Zhihui Liu[3], Xiuquan Liu[1]

[1] College of Mechanical and Electronic Engineering, China University of Petroleum, 266580 Qingdao, China
[2] Faculty of Built Environment, University Malaya, 50603 Kuala Lumpur, Malaysia
[3] School of Petroleum Engineering, China University of Petroleum, 266580 Qingdao, China

[*] Correspondence: Yanqun Yu (yuyq_hdpu@126.com)

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Abstract: To address the challenges in traditional Failure Mode and Effects Analysis (FMEA) related to determining factor weights, identifying risk priority of failure modes, and managing uncertainties in the risk assessment process, this paper proposes an enhanced FMEA risk factor evaluation method. This method integrates incomplete and imprecise expert assessments using a fuzzy multi-criteria compromise ranking technique called the "V1seKriterijumska Optimizacija I Kompromisno Resenje" (VIKOR). By employing Fuzzy Evidence Reasoning (FER), the risk factor ratings are represented using fuzzy belief structures to capture their diversity and uncertainty. Objective weights are adjusted using Shannon entropy to correct subjective weights, and the VIKOR technique is applied to prioritize failure modes based on the principles of minimizing individual regret and maximizing group utility. The improved model is applied to identify key equipment associated with oil and gas leakage risk in the Floating Production Storage and Offloading (FPSO) system. Validity and sensitivity analysis confirm the robustness and reliability of the method, enhancing the accuracy and credibility of the evaluation results.

Keywords: Enhanced Failure Mode and Effects Analysis (FMEA); Risk identification; Fuzzy Evidence Reasoning (FER); Fuzzy multi-criteria compromise ranking technique; VIKOR; Floating Production Storage and Offloading (FPSO) system

1 Introduction

The FPSO system is a complex process system composed of personnel, equipment, processes, and the environment. The systems are strongly interconnected, and damage or failure of a specific piece of equipment or subsystem can easily propagate to other subsystems, thereby disrupting normal operational processes and triggering risks. The entire oil and gas processing operation is a continuously changing dynamic process, with the upper module's complex oil and gas processing equipment inevitably containing numerous potential oil and gas leakage risk sources. Therefore, accurately identifying and assessing critical leakage equipment is particularly important. FMEA is a widely used, reasonable, and efficient qualitative/semi-quantitative risk assessment method. FMEA applies a top-down analysis sequence to establish the relationship between the target object, its failure modes, and the consequences of faults, and conducts risk assessment based on the final evaluation results. This approach allows for the early detection of hazardous instability issues during the design phase of equipment and facilities, enabling the scientific and rational use of resources to reduce the occurrence of unexpected accidents or minimize their impact [1, 2]. FMEA method was first developed and implemented by the U.S. Army in 1949. In the 1970s, its application expanded to the aerospace and automotive industries and later to general manufacturing industries [3].

In conventional FMEA risk identification, the Risk Priority Number (RPN) is used to quantify the severity of different failure modes. The RPN is the product of three risk factors: Severity (S), Occurrence (O), and Indetectability (D). The higher the RPN value, the more dangerous the corresponding failure mode [4]. According to different risk assessment standards, the linguistic descriptions of S, O, and D can be converted into corresponding effective data, which are multiplied to obtain the RPN value. Since the three coefficients are specific values, the RPN is also a precise number. However, this precise number assessment model has certain problems, such as the difficulty of accurately evaluating the three risk factors [5, 6]; different combinations may yield the same result, leading to the same level of risk influence [7, 8]; and the relative weights of the risk factors are not considered, resulting in insufficient credibility of the results.

To overcome one or more limitations of the traditional FMEA method, various scholars have combined fuzzy evidence theory, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), grey relational theory, and Decision-Making Evaluation Laboratory (DEMATEL) theory, among others, to improve FMEA. Seyed-Hosseini et al. [9] proposed a DEMATEL method for FMEA risk priority ranking, with the main advantage of considering the indirect relationships between multiple failure modes and the ability to cluster alternatives, but it does not address the fuzzy issues present in the research environment. Du and Peng [10] proposed a risk analysis method based on FER to address uncertainty in risk rating and FMEA issues, incorporating expert knowledge and experience into the FMEA process to improve the accuracy of analysis while considering the correlation between failure modes. Kang et al. [11] introduced fuzzy set theory and DEMATEL into FMEA, combining it with TOPSIS theory to study and analyze the failure modes of offshore wind turbine facilities, enhancing the credibility of the result. Li et al. [12] evaluated information security in small cities based on trapezoidal fuzzy numbers and grey relational theory. Based on cloud model theory and hierarchical techniques, Liu et al. [13] transformed the linguistic evaluations of failure modes into cloud fuzzy numbers, combining the advantages of cloud models in handling fuzziness and randomness in linguistic evaluations with the advantages of hierarchical TOPSIS in solving complex decision problems. However, there is no relevant research combining the Fuzzy Analytic Hierarchy Process (FAHP) method with FER and TOPSIS, particularly in the failure mode assessment of FMEA, where FER is particularly suitable for handling incomplete assessments with uncertainty.

To determine the weights of risk factors, relevant literature has conducted detailed analyses based on AHP, FAHP, and Analytic Network Process (ANP) methods. Kutlu and Ekmekçioğlu [14] used the FAHP to obtain the proportional weights of risk impact factors, but ignored the objective real data of the risk impact factors. Carpitella et al. [15] derived the relative priority of evaluation criteria in the fuzzy TOPSIS method using AHP to rank failure modes. Boral et al. [16] used Buckley's FAHP method to calculate the fuzzy weights of risk factors. Rezaei [17] proposed the Best-Worst Method (BWM) to flexibly determine the importance weights of criteria, a comparison-based method that establishes comparisons among items in a specific way. Since traditional BWM cannot obtain weights in uncertain environments, fuzzy BWM technology was adopted [18–20]. However, BWM involves a cumbersome process and some pairwise comparisons to achieve consistent results.

In summary, traditional FMEA methods have played an important role in risk identification and risk ranking. However, due to the inaccuracy of their assessments, relevant scholars have conducted extensive research on the processing and ranking of fuzzy data, but the research field remains underdeveloped in the context of incomplete assessments of risk factors. Regarding the weights of risk factors, methods such as FAHP have been introduced, but these only rely on the subjective determination of experts, failing to effectively combine evaluation results and consider the comprehensive determination of risk factors based on the weight of expert evaluations.

In the case of missing or insufficient information, the risk assessment of critical hazardous equipment must consider the evaluation opinions of multiple experts, making more use of experts' experience and knowledge to objectively and accurately conduct risk assessments from multiple perspectives. In response to incomplete or inaccurate expert information, this paper discusses the study of RPN considering different expert evaluation opinions. Therefore, taking HYSY 118 FPSO as an example, this paper discusses the study of risk ranking considering different expert evaluation opinions in the case of incomplete or inaccurate expert information. Specifically, it proposes a method that integrates multiple sources of uncertainty for risk identification to determine the priority order, combining FER, Fuzzy Analytic Hierarchy Process-Entropy Weighting Method (FAHP-EWM) composite weighting, and VIKOR to determine the most reasonable ranking of equipment risk levels. This approach aims to identify the critical leakage equipment in the oil and gas processing system, and the method's effectiveness and sensitivity are verified to confirm its reliability, thereby achieving the goal of improving assessment efficiency. The main advantages of the proposed method are as follows:

-The method combines subjective weighting and objective weighting methods to allocate the weights of each risk factor, not only integrating the experience and knowledge of evaluation experts but also considering the objective information of the influencing factors, making the weight allocation more reasonable.

-The method combines fuzzy set theory with a belief structure model to establish a Fuzzy Belief Structure (FBS) risk model, integrating fuzzy risk evaluation levels with confidence, thereby enabling the quantitative description of qualitative risk information.

-The fuzzy VIKOR method can handle uncertain data and solve fuzzy multi-criteria problems with conflicting and incommensurable criteria, providing a more reasonable formula for calculating the gap between the state of failure modes in FMEA and the ideal point.

2 Research on Risk Identification Method Based on Multi-Source Uncertainty

When conducting FMEA identification, it is essential to accumulate relevant data and summarize complete failure modes and their severity. In cases of missing or insufficient information, qualitative and quantitative risk analysis of key leakage equipment requires the comprehensive evaluation of experts, scholars, and frontline technical personnel. This evaluation should be carried out objectively and meticulously from theoretical, practical, and application perspectives. This paper treats FMEA as a group multi-criteria decision-making (MCDM) problem, based on FER. Fuzzy linguistic variables are used to evaluate the actual performance of N potential failure modes $\mathrm{FM}_i(1 \leq i \leq \mathrm{N})$ in risk factors RF_l (where l=1, 2, 3 represents risk factors S, O, D, respectively) and the relative importance between risk factors. Combining FEA, FAHP-EWM composite weighting, and fuzzy VIKOR techniques, a method is proposed to identify key failure equipment based on stochastic uncertainty and cognitive uncertainty. Figure 1 illustrates all the necessary steps and procedures of the identification method proposed in this paper, with the main specific steps as follows:

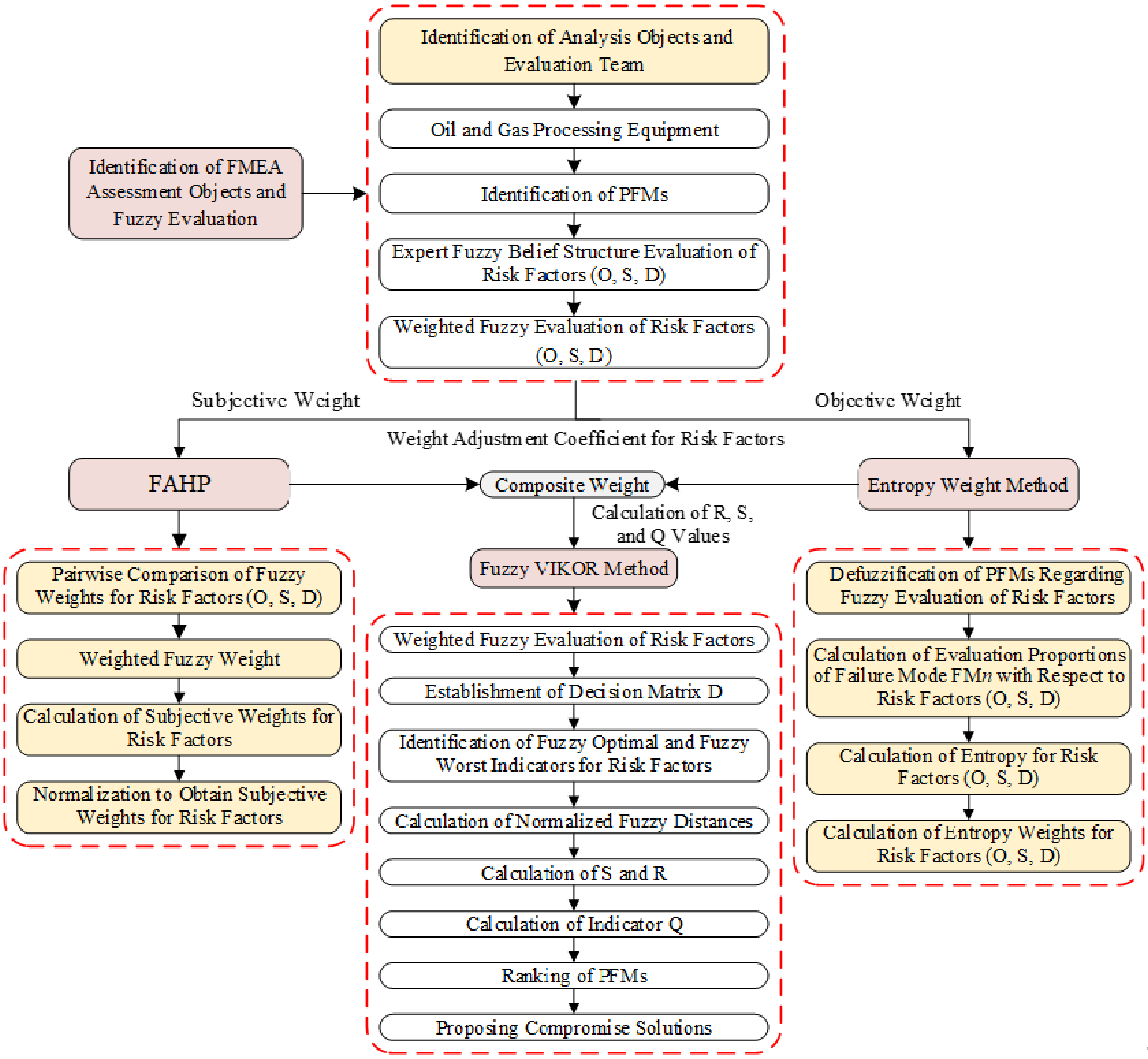

Figure 1. Flowchart of key failure equipment identification method

Step 1: Determine the goal of risk identification, establish the level of analysis, form an FMEA analysis team, list potential failure modes (PFMs), and describe the relevant risk factors.

Step 2: Based on the evaluation linguistic variables, the FMEA team conducts belief assessments for PFMs and integrates expert evaluations to obtain the fuzzy evaluation of failure modes concerning risk factors through weighted calculations.

Step 3: Obtain the subjective weights of risk factors using the FAHP; use the entropy method to obtain the objective weights of risk factors, and thus, obtain the composite weights of risk factors through the weight adjustment coefficient.

Step 4: Summarize the linguistic evaluations of each failure mode and risk factors by the team members, determine the fuzzy best and fuzzy worst indicator values, and calculate the normalized fuzzy distance to obtain the S, R, and Q values, respectively. Rank all failure modes by their risk priority order based on the S, R, and Q values in descending order, thereby obtaining the analysis results.

The following sections will provide a detailed explanation of each analysis step.

2.1 Determination of Research Subjects and Evaluation Experts

First, it is necessary to establish the decision-making expert team. Assume that there are K decision-making experts $(\mathrm{DE}_1, \mathrm{DE}_2, \cdots, \mathrm{DE}_{\mathrm{K}})$ in the FMEA team responsible for the evaluation. In risk assessment, experts from various fields, based on different professional orientations and work experiences, may produce different analytical results when analyzing the same risk factors [21]. To reflect the importance and expertise of each expert in the evaluation process, different weights can be assigned to them. These weights are determined based on the experts' prior information, such as their professional background, application experience, professional competence, familiarity with specific risk factors, and past evaluation performance, to reflect their relative importance within the FMEA team. Different decision experts DE_k are assigned weights that satisfy $\lambda_k > 0 (k = 1, \cdots, \mathrm{K})$ to reflect their relative importance in the FMEA team. $\sum_{k=1}^{\mathrm{K}} \lambda_k = 1$. The determination of expert weights should employ methods such as the direct rating method, point allocation method, and linear programming technique for multidimensional preference analysis (LINMAP). Afterward, the potential oil and gas leakage sources in the system should be identified. The oil and gas processing system includes a large number of process equipment, and for equipment with a high risk of leakage, extensive research and review of its structure, function, and process flow should be conducted with a focus on these aspects.

2.2 Fuzzy Evaluation of Failure Mode Risk Factors Based on FER

To ensure that each evaluation grade is a fuzzy set, linguistic variables are selected when evaluating the risk factors O, S, and D, namely: $\mathrm{H} = \{\mathrm{H}_{11}, \mathrm{H}_{22}, \mathrm{H}_{33}, \mathrm{H}_{44}, \mathrm{H}_{55}, \mathrm{H}_{66}, \mathrm{H}_{77}\}$ = Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H), Very High (VH).

Assume that the fuzzy evaluation grades $\{\mathrm{H}_{ii}\}\,(i = 1, 2, 7)$ are all independent, with only the two adjacent grades being related. The trapezoidal distribution can be used to represent all the evaluation grades. Based on expert opinions, fuzzy numbers can be used to approximate the seven single evaluation grades. Trapezoidal fuzzy numbers are mainly used to solve the membership degree problem, allowing the fuzziness and uncertainty of the evaluation to be expressed in the form of intervals, which is consistent with the reason for using trapezoidal fuzzy numbers in this paper. The operations of trapezoidal fuzzy numbers follow the following rules:

$$\tilde{A} \pm \tilde{B} = (a_1, a_2, a_3, a_4) \pm (b_1, b_2, b_3, b_4) = (a_1 \pm \mathrm{b}_1, a_2 \pm \mathrm{b}_2, a_3 \pm \mathrm{b}_3, a_4 \pm \mathrm{b}_4) \tag{1}$$

$$r\tilde{A} = (ra_1, ra_2, ra_3, ra_4) \tag{2}$$

$$\tilde{A} \otimes \tilde{B} = (a_1 b_1, a_2 b_2, a_3 b_3, a_4 b_4) \tag{3}$$

$$\tilde{A} / \tilde{B} = (a_1/\mathrm{b}_4, a_2/\mathrm{b}_3, a_3/\mathrm{b}_2, a_4/\mathrm{b}_1) \tag{4}$$

where, $\widetilde{A} = (a_1, a_2, a_3, a_4)$ and $\widetilde{B} = (b_1, b_2, b_3, b_4)$ are two trapezoidal fuzzy numbers. The parameter form of $\widetilde{A}$ is $\tilde{A}(\alpha) = \left[\tilde{A}_L(\alpha), \tilde{A}_R(\alpha)\right]$, wherein $\alpha \in [0, 1]$, and there are $\tilde{A}_L(\alpha) = a_1 + (a_2 - a_1)\,\alpha$ and $\tilde{A}_R(\alpha) = a_4 - (a_4 - a_3)\,\alpha$. The parameter form of $\tilde{B}$ is $\tilde{B}(\alpha) = \left[\tilde{B}_L(\alpha), \tilde{B}_R(\alpha)\right]$. The distance between the two fuzzy numbers is defined as follows:

$$d(\tilde{A}, \tilde{B}) = \sqrt{\int_0^1 \left(\tilde{A}_L(\alpha) - \tilde{B}_L(\alpha)\right)^2 d\alpha + \int_0^1 \left(\tilde{A}_R(\alpha) - \tilde{B}_R(\alpha)\right)^2 d\alpha} \tag{5}$$

The membership function value of the fuzzy evaluation can be determined by multiple periods of historical reference through questionnaire surveys, comprehensively determining the specific values based on multiple historical experiences, as shown in Table 1.

The interval fuzzy evaluation grade set $\{\mathrm{H}_{ij}\}\,(i = 1, 2, \cdots, 6; j = i+1, \cdots, 7)$ is defined as the trapezoidal distribution of the fuzzy evaluation grade $(\mathrm{H}_{ii}, \mathrm{H}_{i+1,j+1}, \mathrm{H}_{jj})$. If there exists a trapezoidal distribution for the evaluation grade, the interval evaluation grade formed also presents a trapezoidal distribution, as shown in Figure 2.

Table 1. Linguistic variable evaluation of failure modes

Linguistic Rating	Trapezoidal Fuzzy Number
VL (Very Low)	$(0, 0, 0.1, 0.2)$
L (Low)	$(0.1, 0.2, 0.2, 0.3)$
ML (Medium Low)	$(0.2, 0.3, 0.4, 0.5)$
M (Medium)	$(0.4, 0.5, 0.5, 0.6)$
MH (Medium High)	$(0.5, 0.6, 0.7, 0.8)$
H (High)	$(0.7, 0.8, 0.8, 0.9)$
VH (Very High)	$(0.8, 0.9, 1.0, 1.0)$

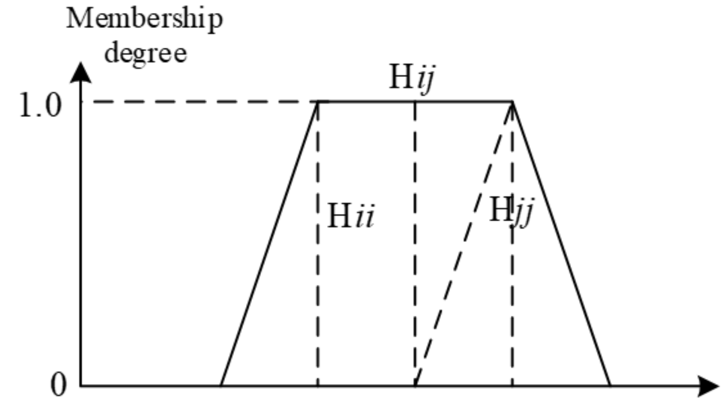

Figure 2. Interval evaluation fuzzy levels

In most cases, the evaluation levels in the FMEA analysis process may represent a fuzzy concept, where the meanings of two adjacent levels do not show a specific difference. The FER method allows FMEA decision experts to provide subjective judgments flexibly. Specifically, the evaluation level of failure mode FM_n by expert DE_k can be expressed as:

$$\left\{\left(\mathrm{H}_{ij}, \mathrm{U}_{ij}^{k}\left(\mathrm{FM}_n, \mathrm{RF}_l\right)\right), i \leq j, i, j=1, \cdots, 7, n=1, \ldots\ldots, \mathrm{N}, l=1,2,3.\right\} \tag{6}$$

where, $\mathrm{U}_{ij}^{k}\left(\mathrm{FM}_n, \mathrm{RF}_l\right)$ represents the belief degree of expert $\mathrm{U}_{ij}^{k}\left(\mathrm{FM}_n, \mathrm{RF}_l\right)$ in evaluating the risk factor RF_l of failure mode FM_n on level H_{ij}. If $\sum_{i=1}^{7}\sum_{j=1}^{7}\mathrm{U}_{ij}^{k}\left(\mathrm{FM}_n, \mathrm{RF}_l\right)=1$, meaning the expert DE_k 's subjective evaluation has a belief degree (also called belief mass) of 1, this evaluation is called a complete evaluation; otherwise, it is an incomplete evaluation. The missing information is referred to as partial ignorance and can be distributed across any level between very low and very high. Particularly, when a decision expert is unwilling or unable to evaluate a specific risk factor for a failure mode, the evaluation can be represented as $\{(\mathrm{H}_{17}, 1.0)\}$. This judgment is called complete ignorance. Clearly, the belief structure in the FER method provides FMEA decision experts with an easy-to-use and highly flexible way to express opinions and can quantify risk factors better than the traditional RPN method.

The comprehensive belief structure obtained by integrating the evaluations of K assessment experts on failure mode FM_n regarding risk factor RF_l can be expressed as:

$$\mathrm{U}_{ij}\left(\mathrm{FM}_n, \mathrm{RF}_l\right)=\sum_{k=1}^{\mathrm{K}}\lambda_k\mathrm{U}_{ij}^{k}\left(\mathrm{FM}_n, \mathrm{RF}_l\right) \tag{7}$$

Therefore, the integrated belief structure of all experts' evaluations can be expressed as:

$$\left\{\left(\mathrm{H}_{ij}, \mathrm{U}_{ij}\left(\mathrm{FM}_n, \mathrm{RF}_l\right)\right), i \leq j, i, j=1, \cdots, 7, n=1, \ldots\ldots, \mathrm{N}, l=1,2,3.\right\} \tag{8}$$

Hence, the fuzzy evaluation of failure mode FM_n regarding risk factor RF_l obtained by weighting the expert opinions is:

$$\tilde{x}_n(l)=\sum_{i=1}^{7}\sum_{j=1}^{7}\mathrm{H}_{ij}\mathrm{U}_{ij}\left(\mathrm{FM}_n, \mathrm{RF}_l\right) \tag{9}$$

where, $n=1,2,\cdots,\mathrm{N}, l=\mathrm{O},\mathrm{S},\mathrm{D}, \tilde{x}_n(l)$ are trapezoidal fuzzy numbers, $\widetilde{x}_n(l)=(a_{nl}, b_{nl}, c_{nl}, d_{nl})$.

2.3 Determination of Composite Weights Based on Subjective and Objective Evaluation

The traditional FMEA has the problem of treating all risk factors equally, without any gradation of importance. Moreover, most improved FMEA methods only consider the subjective or objective weights of risk factors independently. To address these shortcomings, a combined weighting method that integrates the FAHP and EWM is proposed to represent the weights of risk factors. This combined weighting method improves by eliminating the limitations of both subjective and objective weighting, considering both subjective factors and objective factors, which helps to reflect the essential characteristics of risk evaluation in FMEA.

(1) Subjective Weight-FAHP

The classical subjective weight analysis considers the opinions of multiple experts and makes multiple criteria evaluations. Due to the uncertainty of information and human fuzzy perception and cognition, it is challenging to provide accurate numerical standards. FAHP can capture human assessments of fuzziness when dealing with complex multi-attribute decision problems. In the decision-making evaluation process, the subjective textual language of decision-makers becomes an important reference. The weight vector of risk factors can be obtained either directly through assignment or indirectly by using pairwise comparison methods. Here, decision-makers use the linguistic variables in Table 2 to evaluate the weight vectors of risk factors.

Table 2. Linguistic variables for risk factor weight evaluation

Linguistic Variable	Fuzzy Number	Linguistic Variable	Fuzzy Number
Absolutely Strong (AS)	$(2, 5/2, 3)$	Slightly Weak (SW)	$(2/3, 1, 1)$
Very Strong (VS)	$(3/2, 2, 5/2)$	Fairly Weak (FW)	$(1/2, 2/3, 1)$
Fairly Strong (FS)	$(1, 3/2, 2)$	Very Weak (VW)	$(2/5, 1/2, 2/3)$
Slightly Strong (SS)	$(1, 1, 3/2)$	Absolutely Weak (AW)	$(1/3, 2/5, 1/2)$
Equally Important (E)	$(1, 1, 1)$		

Let M_{ij}^k represent the importance degree of risk factor RF_i relative to risk factor RF_j evaluated by expert DE_k, which is a triangular fuzzy number. The steps to calculate the subjective weight of risk factors are as follows:

Step 1: Calculate the fuzzy comprehensive degree value relative to risk factor RF_i using the following formula:

$$S_i = \sum_{j=1}^{3} M_{ij} \otimes \left[\sum_{i=1}^{3} \sum_{j=1}^{3} M_{ij} \right]^{-1} \tag{10}$$

where, the weighted importance degree of risk factor RF_i relative to risk factorRF_j evaluated by comprehensive experts is:

$$M_{ij} = \sum_{k=1}^{\mathrm{K}} \lambda_{\mathrm{k}} M_{ij}^k = (l_{ij}, m_{ij}, u_{ij}) \tag{11}$$

Step 2: Define the possibility degree of the two fuzzy comprehensive intervals of triangular fuzzy numbers $S_i = (l_i, m_i, u_i)$ and $S_j = (l_j, m_j, u_j)$ as:

$$V\left(S_j \geq S_i\right) = \sup_{y \geq x} \left[\min\left(\mu S_j(y), \mu S_i(x)\right)\right] \tag{12}$$

The above equation can also be described as:

$$V\left(S_j \geq S_i\right) = \mathrm{hgt}\left(S_j \bigcap S_i\right) = \mu S_i(d) = \begin{cases} 1 \text{ if } m_j \geq m_i \\ 0 \text{ if } l_i \geq u_j \\ \frac{l_i - u_j}{(m_j - u_j) - (m_i - l_i)}, \text{ others} \end{cases} \tag{13}$$

In the equation above, the point d is located between μS_i and μS_j, and is the coordinate of the highest point of the intersection, as shown in Figure 3. To compare the sizes of S_i and S_j, it is necessary to calculate $V\left(S_i \geq S_j\right)$ and $V\left(S_j \geq S_i\right)$

Step 3: The possibility degree that convex fuzzy number S is greater than K convex fuzzy numbers $S_i (i = 1, \ldots,$ K) can be calculated by the following formula:

$$V\left(S \geq S_1, S_2, \cdots, S_K\right) = \min V\left(S \geq S_i\right), \quad i = 1, 2, \cdots, K \tag{14}$$

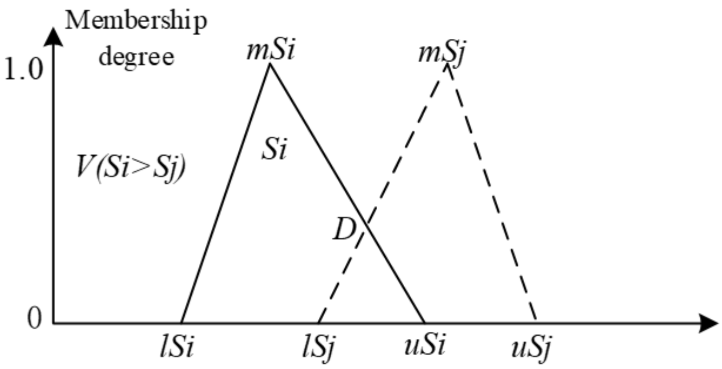

Figure 3. Intersection of S_i and S_j

Step 4: The subjective weight of risk factor $\mathrm{RF}_j(\mathrm{~S}, \mathrm{O}, \mathrm{D})$ can be calculated by the following formula:

$$w^{s^*}=\left(V\left(S_1 \geq S_2, S_3\right), V\left(S_2 \geq S_1, S_3\right), V\left(S_3 \geq S_1, S_2\right)\right)^T \tag{15}$$

After normalization, the result is:

$$w^s=\left(w_S^s, w_O^s, w_D^s\right)^T=\left(\begin{array}{c}\frac{V\left(S_1 \geq S_2, S_3\right)}{V\left(S_1 \geq S_2, S_3\right)+V\left(S_2 \geq S_1, S_3\right)+V\left(S_3 \geq S_1, S_2\right)} \\ \frac{V\left(S_2 \geq S_1, S_3\right)}{V\left(S_1 \geq S_2, S_3\right)+V\left(S_2 \geq S_1, S_3\right)+V\left(S_3 \geq S_1, S_2\right)} \\ \frac{V\left(S_3 \geq S_1, S_2\right)}{V\left(S_1 \geq S_2, S_3\right)+V\left(S_2 \geq S_1, S_3\right)+V\left(S_3 \geq S_1, S_2\right)}\end{array}\right) \tag{16}$$

(2) Objective Weight-EWM

Entropy can measure the disorder degree of a system, and in the process of determining weight values, entropy can be used to judge based on the amount of effective information contained in the data. The method of measuring weight using entropy is called the EWM. EWM allocates weights based on the degree of variation in the evaluation object's values under a certain indicator. If the values of the evaluation objects under a certain indicator vary greatly, then this indicator is more important for distinguishing different objects, and thus should be given a larger weight; conversely, if the values under a certain indicator vary slightly, then this indicator is less important for distinguishing different objects, and should be given a smaller weight.

Firstly, according to the fuzzy evaluation $\tilde{x}_n(l)$ of failure mode FM_n regarding risk factor RF_l, as shown in Eq. (9), the trapezoidal fuzzy number is defuzzified. The most commonly used defuzzification method is applied here, which is the Center of Gravity (COG) defuzzification method [22]. The COG defuzzification method can be expressed by the following formula:

$$x_n(l)=\frac{1}{3}\left[\mathrm{a}_{nl}+b_{nl}+c_{nl}+d_{nl}-\frac{d_{nl} c_{nl}-\mathrm{a}_{nl} b_{nl}}{\left(c_{nl}+d_{nl}\right)-\left(\mathrm{a}_{nl}+b_{nl}\right)}\right] \tag{17}$$

Calculate the evaluation weight ratio of FM_n under the risk assessment indicator RF_l:

$$f_{nl}=\frac{x_n(l)}{\sum_{n=1}^N x_n(l)} \quad n=1,2, \cdots, \mathrm{N}, \cdot l=1,2,3 \tag{18}$$

Thus, the entropy of the RF_l indicator is:

$$H_l=-k \sum_{n=1}^{\mathrm{N}} f_{nl} \ln f_{nl} \tag{19}$$

where, $k=1 / \ln \mathrm{N}$, and assuming $f_{nl}=0$, then $f_{nl} \ln f_{nl}=0$;

The entropy weight w_l^O of the l-th evaluation indicator is obtained as:

$$w_l^O=\frac{1-H_l}{3-\sum_{l=1}^3 H_l} \tag{20}$$

Therefore, the objective weight $w^O=\left(w_S^O, w_O^O, w_D^O\right)^{\mathrm{T}}$.

As an objective weighting method, the main advantage of the entropy weighting method lies in its ability to allocate weights based on the characteristics of the data itself, thereby reducing the impact of subjective judgment. The EWM calculation process is straightforward and clear, and it can reflect the information of the evaluation objects from multiple perspectives, eliminating errors caused by human subjective attitudes, and finding better evaluation indicators with higher discriminative ability. Using the comprehensive weighting method, a weight adjustment coefficient φ is introduced to coordinate subjective and objective weights, and the comprehensive weight is calculated as:

$$\begin{aligned} w &= (w_S, w_O, w_D)^T = \varphi w^s + (1-\varphi) w^o \\ &= (\varphi w_S^s + (1-\varphi) w_S^o, \varphi w_O^s + (1-\varphi) w_O^o, \varphi w_D^s + (1-\varphi) w_D^o)^T \end{aligned} \tag{21}$$

where, $\varphi \in [0,1]$ represents the relative importance between subjective and objective weights. This paper assumes that both weights are equally important, i.e., $\varphi = 0.5$.

2.4 Risk Ranking Based on the Fuzzy Multi-Criteria Compromise Solution Technique

The Multi-Criteria Compromise Solution Technique (VIKOR) was first proposed by Opricovic [23] and Opricovic and Tzeng [24], aiming to select the best alternative from a set of candidate options. By balancing the conflicts between different criteria, VIKOR provides a compromise solution (the closest feasible alternative to the ideal solution) to help decision-makers make an optimal choice [25]. This study proposes an improved fuzzy VIKOR method to handle uncertain data and solve fuzzy multi-criteria problems with conflicting and incommensurable criteria.

The steps of the fuzzy VIKOR method are as follows:

Step 1: Based on the fuzzy evaluation $\tilde{x}_n(l)$ for risk factors regarding failure modes obtained previously, determine the fuzzy best value $\tilde{f}_l^*$ and fuzzy worst value $\tilde{f}_l^-$ for all risk factor indicators, where $l = 1, 2, 3$ represents the risk factors S, O, and D.

$$\tilde{f}_l^* = \left\{ \begin{array}{c} \max_n \tilde{x}_n(l), \text{ Benefit-type} \\ \min_n \tilde{x}_n(l), \text{ Cost-type} \end{array} \right\}, n = 1, 2, \cdots, \mathrm{N} \tag{22}$$

$$\tilde{f}_l^- = \left\{ \begin{array}{c} \min_n \tilde{x}_n(l), \text{ Benefit-type} \\ \max_n \tilde{x}_n(l), \text{ Cost-type} \end{array} \right\}, n = 1, 2, \cdots, \mathrm{N} \tag{23}$$

where, benefit-type indicators represent indicators where higher evaluation values are better, while cost-type indicators represent indicators where lower evaluation values are better. This study is based on FMEA risk value ranking, where lower risk is preferred; therefore, cost-type indicators are used.

Step 2: Calculate the normalized fuzzy distance d_{nl} using Eq. (5):

$$d_{nl} = \frac{d\left(\tilde{f}_l^*, \tilde{x}_n(l)\right)}{d\left(\tilde{f}_l^*, \tilde{f}_l^-\right)} \tag{24}$$

Step 3: Calculate the maximum group utility S_n and the minimum individual regret R_n using the following formulas:

$$S_n = \varphi \sum_{l=1}^{3} w_l^s d_{nl} + (1-\varphi) \sum_{l=1}^{3} w_l^0 d_{nl} = \sum_{l=1}^{3} \left[\varphi w_l^s + (1-\varphi) w_l^0\right] d_{nl} = \sum_{l=1}^{3} w_l d_{nl} \tag{25}$$

$$R_n = \max_l \left[\varphi w_l^s d_{nl} + (1-\varphi) w_l^0 d_{nl}\right] = \max_l \left(w_l d_{nl}\right) \tag{26}$$

where, w_l represents the combined weight of the evaluation criteria, with $l = 1, 2, 3$ representing S, O, and D.

Step 4: Calculate Q_n :

$$Q_n = v \frac{S_n - S^*}{S^- - S^*} + (1-v) \frac{R_n - R^*}{R^- - R^*} \tag{27}$$

where, $S^* = \min_n S_n, S^- = \max_n S_n, R^* = \min_n R_n, R^- = \max_n R_n, v$ is the decision mechanism coefficient, with v representing the weight of the maximum group utility strategy, and $1 - v$ representing the weight of individual regret. In this study, the value of v is set to 0.5 .

Step 5: Rank the failure modes in descending order according to the values of S, R, and Q , where a smaller value indicates lower risk.

Step 6: Determine the compromise minimum failure mode $A^{(1)}$. If the following two conditions are met, the risk ranking based on Q (minimum value) is considered the best.

-Condition 1: $Q\left(A^{(2)}\right)-Q\left(A^{(1)}\right) \geq 1$ /(N-1), where N is the total number of failure modes;

-Condition 2: The failure mode risk $A^{(1)}$ ranking according to S_n and R_n is also low risk, then $A^{(1)}$ is determined as the minimum risk failure mode.

If the above conditions cannot be met simultaneously, two compromise risk ranking situations can be obtained:

(1) If Condition 1 is met but Condition 2 is not, then there are two compromise minimum risks: $A^{(1)}$ and A$^{(2)}$.

(2) If Condition 1 is not met but Condition 2 is, then there are M compromise minimum risks: $A^{(1)}, A^{(2)}, \ldots$, $A^{(M)}$, where the value of M is determined by $Q\left(A^{(M)}\right)-Q\left(A^{(1)}\right)<$ 1/(N-1).

3 Identification of Critical Equipment for Leakage in Oil and Gas Processing Systems

Taking HYSY 118 as the analysis object, the improved FMEA method proposed above is used to identify risks and identify hazardous equipment for oil and gas leakage, thereby laying the foundation for analyzing the mechanism and evolution of fire and explosion accidents.

3.1 HYSY 118 Oil and Gas Processing System

HYSY 118 is a drilling and production platform (DPP) auxiliary platform located in the Enping 24-2 oilfield, connected to the FPSO via subsea mixed transportation flexible pipelines. 30% of the water-containing crude oil and natural gas separated on the DPP platform are transported to the FPSO for further processing, storage, and export. The process treatment system mainly consists of the crude oil treatment system, natural gas treatment system, sewage treatment system, and other auxiliary process systems.

(1) Crude Oil Treatment System

The crude oil treatment system is primarily used to separate water-containing crude oil and to transport the separated crude oil, associated gas, and sewage to other units. The water-containing crude oil from the subsea pipelines is first filtered by the crude oil inlet filter to remove impurities, then heated and enters the first-stage separator. The gas separated in the first-stage separator enters the fuel gas system, the separated water enters the process water tank, and the separated oil is heated again and sent to the second-stage separator. The gas from the second-stage separator enters the flare system, the separated water enters the process water tank, and the separated oil enters the electric dehydration supply pump to be pressurized and returned to the crude oil heat exchanger or the fuel flash system.

(2) Produced Water Treatment System

The produced water treatment system mainly collects and treats oily wastewater to ensure the cleanliness of the discharge water. Produced wastewater is discharged into the sewage treatment tank for oil removal treatment, and the floating oil is pressurized by the oily water pump and sent to the crude oil treatment system. The deoiled wastewater is pressurized by the production pump and transported to the first-stage compact flotation unit, then to the second-stage compact flotation unit. The primary function of these units is to remove oil from the produced water, ultimately reaching discharge standards. The treated production water is discharged to the sea via the open drainage sedimentation tank.

(3) Fuel Gas System

The gas separated from the three-phase separator is mainly natural gas, which typically contains condensate, water vapor, carbon dioxide, and other impurities, and thus must be purified. The purified clean natural gas can be used as fuel, with excess gas sent to the flare exhaust system. The gas from the production separator first enters the associated gas inlet cooler for cooling, then enters the associated gas scrubber for separation and filtration, and is then fed into the heat medium furnace and other fuel gas users.

(4) Auxiliary Process Systems

In addition to the main process systems, the FPSO is also equipped with auxiliary process systems, including the heat medium system, chemical injection system, open and closed drainage systems, etc. The main function of the heat medium system is to heat the medium oil to 220°C and distribute it to various levels of equipment. The flare vent system is used for burning natural gas and venting under emergency conditions. The open drainage system receives overflow liquids, equipment cooling water, and rainwater from various module equipment, which are collected in the open drainage tank and then sent to the oily water tank for treatment. The closed drainage system is mainly used to collect pressurized liquids from process equipment, containers, pipelines, and liquid discharged from safety valves of process equipment containers on the FPSO. The chemical injection system is designed to inject different chemicals at different injection points to prevent corrosion and scaling of equipment and pipelines. The nitrogen generation system mainly provides nitrogen for the topside module of the vessel. The closed-loop cooling system is used to cool the incoming crude oil, fuel gas, and fuel oil and for air conditioning cooling water, using seawater to cool circulating freshwater, and then using the freshwater to cool crude oil and other media.

The oil and gas processing system requires not only the separation of oil, gas, and water phases but also the treatment of produced wastewater, waste gas, etc. This necessitates the coordination and participation of other auxiliary process systems to produce compliant crude oil and ensure sufficient energy for extraction operations.

HYSY 118 adopts an internal turret single-point mooring system, with crude oil input from the turret system at the bow and processed crude oil output from the stern transmission system to shuttle tankers. The topside module is divided into the electrical room module, power station module, heating station module, metering module, water treatment module, oil treatment module 1, oil treatment module 2, and fuel treatment module, among others. The fuel oil treatment module is arranged on the starboard side of the ship and is equipped with fuel crude oil processing facilities and diesel system facilities. The metering module is arranged on the port side of the ship and is equipped with export metering and calibration skids. Oil treatment module 2 is arranged on the starboard side of the ship and is mainly equipped with electric dehydrators and flash devices. Oil treatment module 1 is equipped with first-stage separation, second-stage separation, and fuel gas treatment facilities. The produced water treatment module is arranged on the port side of the ship and is equipped with produced water treatment facilities and a closed-loop cooling system, including the chemical injection system also arranged in this module. According to API RP 505 Recommended Practice for Classification of Locations for Electrical Installations at Petroleum Facilities Classified as Class I, Division 0, Division 1, and Division 2, module B (produced water treatment system and oil treatment module 1), module C (metering module and oil treatment module 2), and module D (fuel oil treatment module) are classified as Class I, Division 2 hazardous areas, as shown in Figure 4.

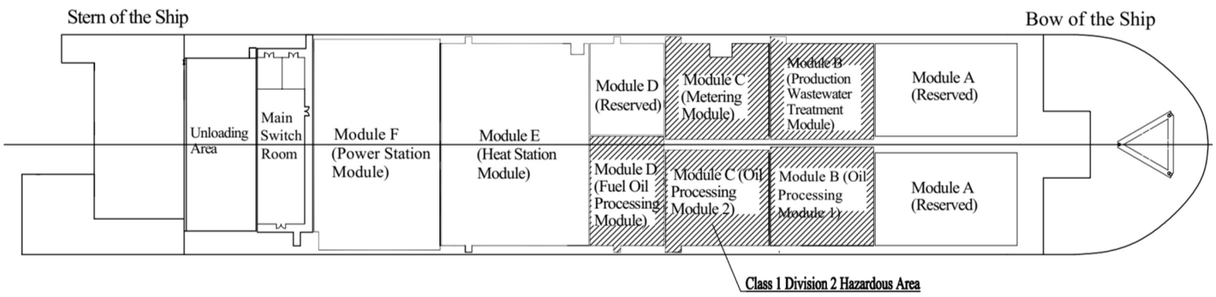

Figure 4. Overall layout of upper modules and hazardous area classification

3.2 Key Equipment for Leakage

To accurately assess the risk level of oil and gas leakage, the expert team must consist of several cross-functional experts who meet the following criteria: having more than 10 years of experience in FPSO design, construction, and inspection; currently engaged in offshore engineering work and scientific research; and possessing advanced knowledge and experience in FPSO systems. Based on these three aspects, the expert team is composed of five experts: Professor DE_1 from Harbin Engineering University specializing in offshore oil and gas safety, Senior Chief Engineer DE_2 from China National Offshore Oil Corporation (CNOOC), Senior Engineer DE_3, Designer DE_4 from CIMC Raffles, and On-site Platform Engineer DE_5. According to the expert weight distribution table, the scores and assigned weights for these five experts are 0.35, 0.2, 0.15, 0.2, and 0.1, respectively.

The FMEA team's function is to determine the equipment prone to oil and gas leakage based on the FPSO process flow and operational characteristics. After repeated verification and comparison, the following 12 pieces of equipment were identified as key objects for leakage risk research: the crude oil heat exchanger skid (FM_1), first-stage separator skid (FM_2), second-stage heater skid (FM_3), second-stage separator skid (FM_4), fuel gas cooler skid (FM_5), fuel gas scrubber skid (FM_6), equipment in Process Area 2 (crude oil metering skid (FM_7), electrostatic desalter skid (FM_8), crude oil cooler skid (FM_9), crude oil flash drum skid (FM_{10}), and equipment in Process Area 3 (crude oil separator skid (FM_{11}), fuel oil filter skid (FM_{12})).

Due to the difficulty in accurately assessing risk factors and the relative importance of their risk factors, the decision-making team performed belief assessments on 12 failure modes. To compare with the results of traditional FMEA, the decision-making team evaluated each risk factor of the failure modes according to the traditional RPN rating standards, as shown in Table 3. The importance judgment of risk factors and the calculation of normalized weights are shown in Table 4. To determine the priority of the 12 risk equipment, decision-making experts made belief assessments for O, S, and D, and the evaluation results are shown in Table 5.

Based on the expert evaluation results, the expert-weighted fuzzy belief assessments obtained using fuzzy evidence belief structure are calculated according to Eqs. (6) to (9), as shown in Table 6.

Table 3. Traditional failure mode RPN evaluation

Failure Mode	$\mathbf{FM_1}$	$\mathbf{FM_2}$	$\mathbf{FM_3}$	$\mathbf{FM_4}$	$\mathbf{FM_5}$	$\mathbf{FM_6}$	$\mathbf{FM_7}$	$\mathbf{FM_8}$	$\mathbf{FM_9}$	$\mathbf{FM_{10}}$	$\mathbf{FM_{11}}$	$\mathbf{FM_{12}}$
S	5	6	5	6	6	6	3	4	5	4	6	4
O	5	7	6	4	5	7	4	4	4	3	5	2
D	3	5	6	6	4	3	4	3	3	4	3	4
RPN	75	210	180	144	120	126	48	48	60	48	90	32

Table 4. Subjective weight assessment of risk factors

Risk Factor	**Severity (S)**	**Occurrence (O)**	**Indetectability (D)**	w^s
Severity (S)	E, E, E, E, E	SW, SW, E, E, FW	VS, E, FS, FS, SS	0.382
Occurrence (O)	-	E, E, E, E, E	SS, E, VS, SS, SS	0.462
Indetectability (D)	-	-	E, E, E, E, E	0.156

Table 5. Fuzzy belief assessment of failure modes

Risk Factor	**Expert**	$\mathbf{FM_1}$	$\mathbf{FM_2}$	$\mathbf{FM_3}$	$\mathbf{FM_4}$	$\mathbf{FM_5}$	$\mathbf{FM_6}$
S	DE_1	$\mathrm{H}_{22}, 0.4$ $\mathrm{H}_{33}, 0.5$	$\mathrm{H}_{35}, 0.9$	H_{33}	H_{34}	H_{45}	$\mathrm{H}_{45,0.9}$
	DE_2	H_{44}	H_{55}	H_{34}	H_{35}	H_{44}	H_{45}
	DE_3	H_{44}	H_{45}	H_{33}	H_{34}	$\mathrm{H}_{33}, 0.2$ $\mathrm{H}_{44}, 0.6$	H_{34}
	DE_4	H_{34}	H_{55}	H_{44}	H_{35}	H_{44}	H_{44}
	DE_5	H_{44}	$\mathrm{H}_{44}, 0.5$ $\mathrm{H}_{55}, 0.5$	H_{34}	H_{44}	H_{44}	H_{45}
0	DE_1	H_{22}	H_{33}	$\mathrm{H}_{33}, 0.5$	$\mathrm{H}_{22}, 0.9$ $\mathrm{H}_{33}, 0.1$	H_{33}	$\mathrm{H}_{33}, 0.5$ $\mathrm{H}_{44}, 0.5$
	DE_2	H_{33}	H_{44}	H_{33}	$\mathrm{H}_{34}, 0, 8$	H_{34}	H_{23}
	DE_3	$\mathrm{H}_{33}, 0.9$	H_{15}	H_{33}	H_{15}	H_{23}	H_{33}
	DE_4	$\mathrm{H}_{34}, 0.7$ $\mathrm{H}_{4}, 0.3$	H_{34}	H_{34}	H_{33}	H_{33}	H_{23}
	DE_5	H_{22}	H_{25}	H_{34}	$\mathrm{H}_{34}, 0.7$ $\mathrm{H}_{33}, 0.2$	H_{33}	H_{22}
D	DE_1	H_{23}	H_{33}	H_{33}	H_{23}	H_{33}	H_{33}
	DE_2	$\mathrm{H}_{33}, 0.9$	H_{34}	H_{33}	H_{22}	$\mathrm{H}_{23}, 0.8$	$\mathrm{H}_{44,0.9}$
	DE_3	H_{22}	H_{33}	H_{22}	H_{22}	H_{33}	H_{24}
	DE_4	H_{22}	H_{22}	H_{23}	H_{12}	H_{23}	H_{34}
	DE_5	H_{22}	H_{23}	H_{33}	H_{12}	H_{33}	$\mathrm{H}_{33}, 0.9$
Risk Factor	**Expert**	$\mathbf{FM_7}$	$\mathbf{FM_8}$	$\mathbf{FM_9}$	$\mathbf{FM_{10}}$	$\mathbf{FM_{11}}$	$\mathbf{FM_{12}}$
S	DE_1	H_{22}	H_{34}	H_{34}	H_{23}	H_{34}	H_{44}
	DE_2	H_{13}	H_{33}	H_{33}	H_{33}	H_{33}	H_{33}
	DE_3	H_{22}	H_{45}	H_{33}	H_{34}	$\mathrm{H}_{23}, 0.5$	$\mathrm{H}_{33}, 0.9$
	DE_4	H_{23}	H_{33}	H_{44}	H_{23}	H_{44}	H_{33}
	DE_5	H_{22}	H_{44}	H_{34}	H_{33}	H_{33}	H_{34}
0	DE_1	H_{22}	H_{22}	$\mathrm{H}_{22}, 0.7$ $\mathrm{H}_{33}, 0.3$	$\mathrm{H}_{22}, 0.9$	$\mathrm{H}_{23}, 0.5$	$\mathrm{H}_{12}, 0.9$
	DE_2	H_{23}	H_{22}	H_{22}	H_{23}	H_{12}	H_{22}
	DE_3	H_{23}	H_{23}	H_{33}	H_{33}	H_{13}	$\mathrm{H}_{12}, 0.9$
	DE_4	H_{22}	H_{33}	H_{33}	H_{34}	$\mathrm{H}_{23}, 0.5$	H_{12}
	DE_5	H_{12}	H_{22}	H_{23}	H_{22}	$\mathrm{H}_{22,0.9}$	H_{22}
D	DE_1	H_{33}	H_{22}	H_{33}	H_{23}	H_{22}	H_{23}
	DE_2	H_{23}	H_{22}	H_{23}	H_{22}	H_{22}	H_{23}
	DE_3	H_{33}	H_{23}	H_{22}	H_{23}	H_{23}	$\mathrm{H}_{12}, 0.8$
	DE_4	H_{33}	H_{22}	H_{15}	H_{22}	H_{15}	H_{33}
	DE_5	H_{24}	H_{24}	H_{22}	H_{12}	H_{14}	H_{22}

Table 6. Comprehensive fuzzy evaluation of failure modes

Failure Mode	S	O	D
FM_1	$(0.269, 0.366, 0.458, 0.555)$	$(0.164, 0.263, 0.351, 0.450)$	$(0.116, 0.214, 0.322, 0.420)$
FM_2	$(0.368, 0.465, 0.701, 0.797)$	$(0.200, 0.285, 0.515, 0.615)$	$(0.170, 0.270, 0.380, 0.480)$
FM_3	$(0.240, 0.340, 0.450, 0.550)$	$(0.165, 0.248, 0.535, 0.618)$	$(0.165, 0.265, 0.370, 0.470)$
FM_4	$(0.218, 0.310, 0.500, 0.593)$	$(0.037, 0.073, 0.513, 0.585)$	$(0.070, 0.140, 0.360, 0.460)$
FM_5	$(0.382, 0.479, 0.582, 0.679)$	$(0.185, 0.285, 0.420, 0.520)$	$(0.156, 0.252, 0.424, 0.520)$
FM_6	$(0.356, 0.453, 0.641, 0.737)$	$(0.185, 0.285, 0.398, 0.498)$	$(0.215, 0.312, 0.471, 0.568)$
FM_7	$(0.080, 0.160, 0.280, 0.380)$	$(0.090, 0.180, 0.270, 0.370)$	$(0.170, 0.270, 0.410, 0.510)$
FM_8	$(0.250, 0.350, 0.490, 0.590)$	$(0.120, 0.220, 0.270, 0.370)$	$(0.100, 0.200, 0.260, 0.360)$
FM_9	$(0.240, 0.340, 0.465, 0.565)$	$(0.146, 0.246, 0.311, 0.411)$	$(0.115, 0.195, 0.410, 0.510)$
FM_{10}	$(0.145, 0.245, 0.415, 0.515)$	$(0.132, 0.228, 0.358, 0.455)$	$(0.090, 0.180, 0.300, 0.400)$
FM_{11}	$(0.220, 0.320, 0.580, 0.680)$	$(0.129, 0.209, 0.435, 0.530)$	$(0.070, 0.140, 0.270, 0.370)$
FM_{12}	$(0.267, 0.366, 0.454, 0.553)$	$(0.030, 0.060, 0.240, 0.335)$	$(0.105, 0.190, 0.374, 0.471)$

Based on the experts' evaluation results of the failure modes, and combined with the entropy weight method, the objective weights for the evaluation factors are given as $w^0 = (0.3871, 0.3797, 0.2331)$.

For cost-type indicators, the fuzzy best values $\tilde{f}_l^*$ and fuzzy worst values $\tilde{f}_l^-$ are as follows:

$$\widetilde{f}_S^* = (0.08, 0.16, 0.28, 0.38); \widetilde{f}_O^* = (0.03, 0.06, 0.24, 0.335); \widetilde{f}_D^* = (0.07, 0.14, 0.27, 0.37)$$
$$\tilde{f}_S^- = (0.368, 0.465, 0.701, 0.797); \widetilde{f}_S^- = (0.2, 0.285, 0.515, 0.615); \widetilde{f}_S^- = (0.215, 0.312, 0.47, 0.568)$$

The normalized fuzzy distances are calculated, as shown in Table 7. Subsequently, the S, R, and Q values for all failure modes are computed and presented in Table 8. Finally, the risk priority ranking of the failure modes based on the decreasing order of S, R, and Q values is shown in Table 9.

Table 7. Normalized fuzzy distances of failure modes

Failure Mode	S	O	D
FM_1	0.517	0.714	0.964
FM_2	1.000	1.197	1.264
FM_3	0.469	1.162	1.218
FM_4	0.506	0.918	1.084
FM_5	0.842	0.927	1.399
FM_6	0.892	0.874	1.672
FM_7	0.001	0.341	1.377
FM_8	0.539	0.459	0.726
FM_9	0.490	0.592	1.304
FM_{10}	0.301	0.634	0.859
FM_{11}	0.654	0.812	0.736
FM_{12}	0.510	0.001	1.148

Table 8. S, R, and Q values of failure modes

Failure Mode	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7	FM_8	FM_9	FM_{10}	FM_{11}	FM_{12}
S	0.686	1.134	0.906	0.792	0.986	1.036	0.412	0.542	0.691	0.550	0.736	0.420
R	0.300	0.503	0.489	0.386	0.390	0.368	0.268	0.207	0.254	0.267	0.342	0.223
Q	0.348	1.000	0.818	0.565	0.706	0.704	0.102	0.090	0.272	0.196	0.451	0.033

According to Table 9, the comprehensive risk priority ranking of the 12 failure modes is as follows: FM_2: First-stage separator skid $>$ FM_3: Second-stage heater skid $>$ FM_5: Fuel gas cooler skid $>$ FM_6: Fuel gas scrubber skid $>$ FM_4: Second-stage separator skid $>$ FM_{11}: Crude oil separator skid $>$ FM_1: Crude oil heat exchanger skid > FM: Crude oil cooler skid > FM_{10}: Crude oil flash separator skid $>$ FM_7: Crude oil measurement skid $>$ FM_8: Electro-dehydrator skid $>$ FM_{12}: Fuel oil filter skid. Therefore, equipment with higher natural gas leakage risks includes the first-stage separator, fuel gas cooler, and fuel gas scrubber, while equipment with higher crude oil leakage risks includes the second-stage heater, second-stage separator, and crude oil separator. During the production process, more attention should be paid to sealing, overpressure, and corrosion-related material leakage issues in equipment such as the first-stage separator and heater in the crude oil processing system.

Table 9. Ranking of failure modes in descending order of S, R, and Q

Failure Mode	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7	FM_8	FM_9	FM_{10}	FM_{11}	FM_{12}
S	8	1	4	5	3	2	12	10	7	9	6	11
R	7	1	2	4	3	5	8	12	10	9	6	11
Q	7	1	2	5	3	4	10	11	8	9	6	12
RPN	7	1	2	3	5	4	9	9	8	9	6	12

3.3 Sensitivity Analysis

In the proposed FMEA model, the parameter v is introduced as the weight for the group utility maximization strategy. This parameter plays a crucial role in the ranking of failure modes. Generally, v is set to 0.5 , but it can take any value between 0 and 1 . Therefore, it is necessary to perform a sensitivity analysis on the parameter v to verify the obtained results. The related ranking results for different values of v are shown in Figure 5.

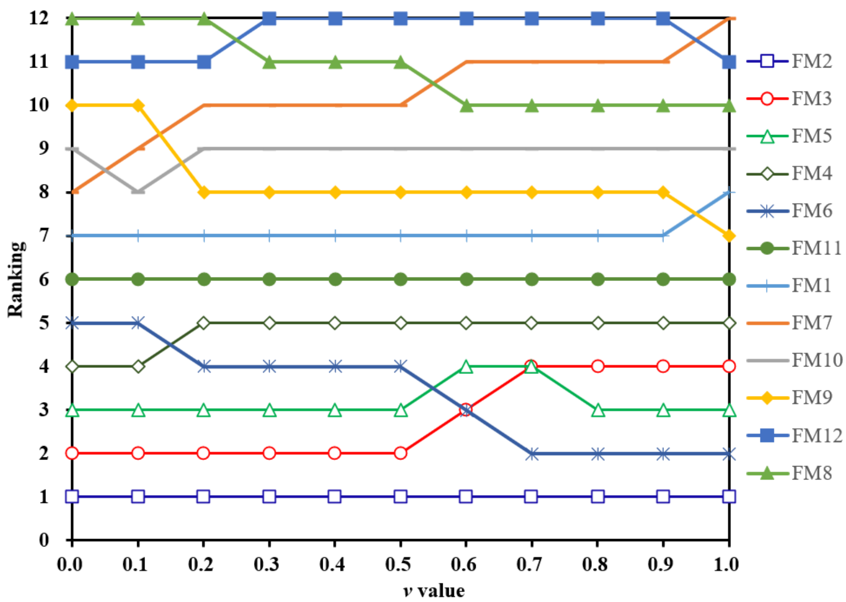

Figure 5. Sensitivity analysis of failure mode ranking

The ranking of FM_2 is not affected by the value of v, and the rankings of FM_3 and FM_5 are not affected when $v \leq 0.5$, indicating that the evaluation results are stable. This shows that the proposed method has good robustness and reliability. Additionally, the ranking of the crude oil cooler skid (FM_9) increases with the value of v. This fact indicates that FM_9 has a higher risk level when focusing on maximizing the utility of the group. Furthermore, when the value of v is smaller, the ranking of the secondary separator skid (FM_4) is higher, indicating that the ranking of FM_4 increases when the importance of minimizing individual regret is higher. In other words, when the minimum individual regret is considered important, its risk level is higher.

4 Comparison and Discussion

According to the research findings of Liu et al. [26], the most commonly used method in FMEA is the Fuzzy Rule Base System (FRBs), followed by MCDM and other integrated methods and mathematical programming methods. However, FRBs have the following limitations: (1) Difficulty in determining appropriate membership functions for risk factors and risk priority; (2) Difficulty in constructing fuzzy if-then rule bases, with high costs and long time consumption; (3) The method cannot distinguish between different fuzzy if-then rules with the same outcome but different premises. Additionally, while methods like AHP address the issue of unequal weights of risk factors, they do not consider data uncertainty. Furthermore, mathematical programming methods, such as fuzzy Data Envelopment Analysis (DEA), face issues with computational complexity and lack of a complete prioritization. In distance-based methods (e.g., TOPSIS), the ranking of failures is based on Euclidean distance measurements from alternatives to the ideal target, and it does not consider the relative importance of these distances [27], while the VIKOR method addresses this limitation.

Table 9 shows the comprehensive risk ranking of 12 devices. It can be seen from the table that the rankings in this method differ from those in conventional methods. One reason for this difference is that traditional FMEA assumes that failure modes with the same RPN have similar risk levels (although they have inherently different risks), while the proposed method considers these inherent differences and assigns different levels to them. For example, $\mathrm{FM}_4(\mathrm{RPN}=144)$ ranks 3rd in conventional FMEA but 5th in the proposed method. On the other hand, $\mathrm{FM}_5(\mathrm{RPN}=120)$ ranks 3rd in the proposed method. Although it seems reasonable for failure modes with higher RPN values to have higher priority, the proposed method assigns a lower priority to FM_4, which has a higher RPN. One reason for this difference is the use of weighted factors for risk factors in the proposed method. The conventional risk factor evaluations for FM_4 are: $(\mathrm{S}=6, \mathrm{O}=4, \mathrm{D}=6)$, and for $\mathrm{FM}_5:(\mathrm{S}=6, \mathrm{O}=5, \mathrm{D}=4)$. Since the weights for severity (S) and occurrence (O) are 0.385 and 0.421, respectively, they are given higher priority.

Furthermore, in traditional FMEA analysis methods, $\mathrm{FM}_7, \mathrm{FM}_8$, and FM_{10} have the same RPN values. However, the proposed method achieves different priority rankings, which traditional methods cannot handle and cannot differentiate between two failure modes. The proposed method effectively addresses this issue and ranks the three failure modes differently. This is due to the basic principle of VIKOR for ranking alternatives. VIKOR is based on an aggregation function that represents "closeness to ideal," based on a compromise programming approach. The VIKOR method determines a compromise solution that provides the maximum "group utility" for the "majority" and the minimum individual regret for the "opponent." As aggregated fuzzy values, $\mathrm{FM}_7, \mathrm{FM}_8$, and FM_{10} have different fuzzy evaluations of failure, and the intimate distances calculated by VIKOR provide different priority rankings for failures. The novelty of the method and the different priority rankings obtained within the framework of composite subjective and objective weights.

5 Conclusions

Based on the HYSY 118 oil and gas processing system process flow, equipment layout, and process hazard areas, this paper proposes a method for identifying key equipment for oil and gas leakage FMEA based on uncertainty and fuzziness, and the following conclusions are drawn:

(1) Based on fuzzy belief structure to resolve the fuzziness of expert judgment and composite weights combining subjective and objective factors to handle the relative importance of risk factors, the application of fuzzy multi-criteria compromise solution ranking method achieves the prioritization of failure modes, thus providing a compromise solution for decision-makers. Sensitivity analysis confirms the reliability of the data obtained from this framework in practical applications.

(2) Compared with other evaluation methods, the proposed evaluation method effectively addresses the fuzziness and random uncertainty in qualitative evaluations, overcoming deficiencies such as difficulty in obtaining accurate values and ignoring evaluation factor weights in conventional FMEA, thus improving the accuracy and credibility of the evaluation results. The method is also applicable to other similar risk identification processes that require the integration of expert judgment and handling of fuzziness and subjectivity.

(3) The comprehensive equipment identification method shows that the key equipment for natural gas leakage includes the primary separator, fuel gas scrubber, and fuel gas cooler, while the key equipment for crude oil leakage mainly includes the secondary heater, secondary separator, and crude oil separator. During the production process, more attention should be paid to the sealing, overpressure, and corrosion-induced material leakage of equipment such as the primary separator and heater in the crude oil processing system.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] H. Zhang, Y. Dong, J. Xiao, F. Chiclana, and E. Herrera-Viedma, "Consensus and opinion evolution-based failure mode and effect analysis approach for reliability management in social network and uncertainty contexts," *Reliab. Eng. Syst. Saf.*, vol. 208, p. 107425, 2021. https://doi.org/10.1016/j.ress.2020.107425

[2] P. Zhang, Z. J. Zhang, and D. Q. Gong, "An improved failure mode and effect analysis method for group decision-making in utility tunnels construction project risk evaluation," *Reliab. Eng. Syst. Saf.*, vol. 244, p. 109943, 2024. https://doi.org/10.1016/j.ress.2024.109943

[3] J. Huang, J. X. You, H. C. Liu, and M. S. Song, "Failure mode and effect analysis improvement: A systematic literature review and future research agenda," *Reliab. Eng. Syst. Saf.*, vol. 199, p. 106885, 2020. https://doi.org/10.1016/j.ress.2020.106885

[4] H. C. Liu, X. Q. Chen, J. X. You, and Z. Li, "A new integrated approach for risk evaluation and classification with dynamic expert weights," *IEEE Trans. Reliab.*, vol. 70, no. 1, pp. 163–174, 2020. https://doi.org/10.1109/TR.2020.2973403

[5] Z. Yang, S. Bonsall, and J. Wang, "Fuzzy rule-based bayesian reasoning approach for prioritization of failures in FMEA," *IEEE Trans. Reliab.*, vol. 57, no. 3, pp. 517–528, 2008. https://doi.org/10.1109/TR.2008.928208

[6] H. Gargama and S. K. Chaturvedi, "Criticality assessment models for failure mode effects and criticality analysis using fuzzy logic," *IEEE Trans. Reliab.*, vol. 60, no. 1, pp. 102–110, 2011. https://doi.org/10.1109/TR.2010.2103672

[7] H. C. Liu, L. Liu, Q. H. Bian, Q. L. Lin, N. Dong, and P. C. Xu, "Failure mode and effects analysis using fuzzy evidential reasoning approach and grey theory," *Expert Syst. Appl.*, vol. 38, no. 4, pp. 4403–4415, 2011. https://doi.org/10.1016/j.eswa.2010.09.110

[8] Z. Zhang and X. Chu, "Risk prioritization in failure mode and effects analysis under uncertainty," *Expert Syst. Appl.*, vol. 38, no. 1, pp. 206–214, 2011. https://doi.org/10.1016/j.eswa.2010.06.046

[9] S. M. Seyed-Hosseini, N. Safaei, and M. J. Asgharpour, "Reprioritization of failures in a system failure mode and effects analysis by decision making trial and evaluation laboratory technique," *Reliab. Eng. Syst. Saf.*, vol. 91, no. 8, pp. 872–881, 2006. https://doi.org/10.1016/j.ress.2005.09.005

[10] H. H. Du and C. Peng, "Failure mode and effects analysis method based on fuzzy TOPSIS," *J. Beijing Univ. Aeronaut. Astronaut.*, vol. 42, no. 2, pp. 368–374, 2016. https://doi.org/10.13700/j.bh.1001-5965.2015.0088

[11] J. Kang, L. Sun, H. Sun, and C. Wu, "Risk assessment of floating offshore wind turbine based on correlation-FMEA," *Ocean Eng.*, vol. 129, pp. 382–388, 2017. https://doi.org/10.1016/j.oceaneng.2016.11.048

[12] X. Li, G. Chen, S. Jiang, R. He, C. Xu, and H. Zhu, "Developing a dynamic model for risk analysis under uncertainty: Case of third-party damage on subsea pipelines," *J. Loss Prev. Process Ind.*, vol. 54, pp. 289–302, 2018. https://doi.org/10.1016/j.jlp.2018.05.001

[13] H. C. Liu, L. E. Wang, Z. Li, and Y. P. Hu, "Improving risk evaluation in FMEA with cloud model and hierarchical TOPSIS method," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 1, pp. 84–95, 2018. https://doi.org/10.1109/TFUZZ.2018.2861719

[14] A. C. Kutlu and M. Ekmekçioğlu, "Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP," *Expert Syst. Appl.*, vol. 39, no. 1, pp. 61–67, 2012. https://doi.org/10.1016/j.eswa.2011.06.044

[15] S. Carpitella, A. Certa, J. Izquierdo, and C. M. La Fata, "A combined multi-criteria approach to support FMECA analyses: A real-world case," *Reliab. Eng. Syst. Saf.*, vol. 169, pp. 394–402, 2018. https://doi.org/10.1016/j.ress.2017.09.017

[16] S. Boral, I. Howard, S. K. Chaturvedi, K. McKee, and V. N. A. Naikan, "An integrated approach for fuzzy failure modes and effects analysis using fuzzy AHP and fuzzy MAIRCA," *Eng. Fail. Anal.*, vol. 108, p. 104195, 2020. https://doi.org/10.1016/j.engfailanal.2019.104195

[17] J. Rezaei, "Best-worst multi-criteria decision-making method," *Omega*, vol. 53, pp. 49–57, 2015. https://doi.org/10.1016/j.omega.2014.11.009

[18] S. Guo and H. Zhao, "Fuzzy best-worst multi-criteria decision-making method and its applications," *Knowl.-Based Syst.*, vol. 121, pp. 23–31, 2017. https://doi.org/10.1016/j.knosys.2017.01.010

[19] Z. Tian, J. Wang, and H. Zhang, "An integrated approach for failure mode and effects analysis based on fuzzy best-worst, relative entropy, and VIKOR methods," *Appl. Soft Comput.*, vol. 72, pp. 636–646, 2018. https://doi.org/10.1016/j.asoc.2018.03.037

[20] A. Hafezalkotob and A. Hafezalkotob, "A novel approach for combination of individual and group decisions based on fuzzy best-worst method," *Appl. Soft Comput.*, vol. 59, pp. 316–325, 2017. https://doi.org/10.1016/j.asoc.2017.05.036

[21] K. Xu, L. C. Tang, M. Xie, S. L. Ho, and M. L. Zhu, "Fuzzy assessment of FMEA for engine systems," *Reliab. Eng. Syst. Saf.*, vol. 75, no. 1, pp. 17–29, 2002. https://doi.org/10.1016/S0951-8320(01)00101-6

[22] H. T. Nguyen and N. R. Prasad, *Fuzzy Modeling and Control: Selected Works of Sugeno*. CRC Press, 1999.

[23] S. Opricovic, "Multicriteria optimization of civil engineering systems," *Fac. Civ. Eng., Belgrade*, vol. 2, no. 1, pp. 5–21, 1998.

[24] S. Opricovic and G. H. Tzeng, "Multicriteria planning of post-earthquake sustainable reconstruction," *Comput.-Aided Civ. Infrastruct. Eng.*, vol. 17, no. 3, pp. 211–220, 2002. https://doi.org/10.1111/1467-8667.00269

[25] S. Opricovic and G. H. Tzeng, "Extended VIKOR method in comparison with outranking methods," *Eur. J. Oper. Res.*, vol. 178, no. 2, pp. 514–529, 2007. https://doi.org/10.1016/j.ejor.2006.01.020

[26] H. C. Liu, L. Liu, and N. Liu, “Risk evaluation approaches in failure mode and effects analysis: A literature review,” *Expert Syst. Appl.*, vol. 40, no. 2, pp. 828–838, 2013. https://doi.org/10.1016/j.eswa.2012.08.010
[27] N. Zhang and G. Wei, “Extension of VIKOR method for decision making problem based on hesitant fuzzy set,” *Appl. Math. Model.*, vol. 37, no. 7, pp. 4938–4947, 2013. https://doi.org/10.1016/j.apm.2012.10.002