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Risk Identification of FPSO Oil and Gas Processing System Based on an Improved FMEA Approach

Longting Wang [1,2], Liping Sun [1], Jichuan Kang [1,*], Yanfu Wang [2] and Haiqing Wang [2]

[1] College of Shipbuilding Engineering, Harbin Engineering University, Harbin 150001, China; wanglt@upc.edu.cn (L.W.); sunliping@hrbeu.edu.cn (L.S.)
[2] College of Mechanical and Electronic Engineering, China University of Petroleum, Qingdao 266580, China; wangyanfu@upc.edu.cn (Y.W.); wanghaiqing@upc.edu.cn (H.W.)
* Correspondence: kangjichuan@hrbeu.edu.cn; Tel.: +86-0451-8251-8398

Abstract: It is increasingly necessary to perform risk analysis in marine structures, to ensure system safety, as they are large and complex. In view of the shortcomings of failure mode and effect analysis (FMEA), a modified fuzzy TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) approach is proposed that is based on fuzzy evidence reasoning (FER), and considers the risk factor rating and relative weight. The presented method is used to prioritize the risk of equipment failure modes for the floating production storage and offloading system (FPSO) oil and gas processing system. The subjective weights and objective weights of occurrence (O), severity (S), and detectability (D) have been considered comprehensively. The subjective experience of the experts and the objective information reflected by the O, S, and D ratings are all included in the weights, making the ranking results closer to reality. The results can be scientific references for decision-makers in risk identification.

Keywords: FPSO oil and gas processing system; failure mode and effect analysis (FMEA); fuzzy evidence reasoning (FER); fuzzy TOPSIS; comprehensive weighting method

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1. Introduction

One of the mainstream methods for offshore oil and gas development is the floating production storage and offloading system (FPSO). It consists of more than a dozen large systems such as subsea, hull, mooring positioning, oil and gas processing, power, fire monitoring, oil storage and transportation, living system, and others. The flammable and explosive characteristics of oil and gas make the oil and gas processing system the most important high-risk system, which may cause fire and explosion accidents, like the 2015 explosion accident of Cidade de São Mateus FPSO in Brazil, which resulted in nine deaths and 26 injuries [1–3]. Consequently, it is important to identify the oil and gas leakage risk of the FPSO oil and gas processing system.

Failure mode and effect analysis (FMEA) has been used widely as a critical safety and reliability analysis tool in various industries, especially in the aerospace, automotive, nuclear, and healthcare industries [4–7]. Conventionally, the ranking of failure modes for corrective actions is determined in terms of the risk priority number (RPN), which is the result of the mathematical product of occurrence (O), severity (S), and detectability (D). Here, O represents the frequency of the risk, D indicates the possibility of predicting the risk before it occurs, and S indicates the severity of the risk to the system [8].

However, the conventional RPN method has several limitations and causes many problems. The major ones are summarized as follows [9–12]: (1) O, S, and D are considered to be equally weighted, without considering the relative importance between them; (2) since areas of expertise may vary depending on the experience of the evaluator, it is difficult to identify O, S, and D accurately; (3) there is no scientific basis for calculating RPN by multiplying O, S, and D; and (4) the same RPN may be produced by different combinations of O, S, and D. In fact, 120 different RPN values can be calculated from O, S, and D, and many of the numbers are in the range of 1–1000. The RPN elements have many duplicate numbers as well. Hence, the mathematical formula for calculating RPN is questionable and debatable. (5) RPN uses only three risk factors to evaluate safety, but the other important risk factors, such as the economic direction of the error, are not considered. The AIAG/VDA (Automotive Industry Action Group/Verband der Automobilindustrie) FMEA Handbook [13] recommends using action priority (AP) fields in place of the RPN in design failure mode and effects analysis (DFMEA), potential failure mode and effects analysis (PFMEA), and FMEA for monitoring and system response (FMEA-MSR) to evaluate priority for actions. The AP also provides all 1000 possible combinations of S, O, and D; and the AP table recommends that measures be classified into high priority (H), medium priority (M), and low priority (L). In essence, AP has the same disadvantages and problems as the traditional RPN.

In order to overcome one or more of the limitations and to improve the effectiveness of the traditional FMEA methods, several scholars have carried out the risk ranking of failure modes by combining fuzzy evidence theory, Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) theory, grey correlation theory, Decision-Making Trial and Evaluation Laboratory (DEMATEL) theory, and other methods. Seyed-Hosseini et al. [14] proposed the DEMATEL method to be applied in FMEA risk priority sequencing. Chin et al. [15] developed the FMEA method based on the evidential reasoning method to simulate the diversity and uncertainty of rating in the process of FMEA analysis. Sachdeva et al. [16] proposed the TOPSIS method to rank the risk priority of all failure modes. Du and Peng [17] presented a risk analysis method based on fuzzy evidence reasoning aiming at the uncertainty of risk rating and the question of FMEA. Considering the correlation between failure modes, Kang et al. [18] introduced fuzzy set theory and decision test, and an experimental evaluation method into FMEA, and combined it with TOPSIS theory to analyze the failure modes of offshore wind turbine, to improve the credibility of the results. The information safety of small cities was evaluated by Li et al. [19] based on trapezoidal fuzzy numbers and grey correlation theory. Based on cloud model theory and hierarchical technology, Liu et al. [20] converted the linguistic evaluation of failure modes into cloud fuzzy numbers, combining the advantages of cloud model in dealing with the fuzziness and randomness of linguistic evaluation, and the advantages of hierarchical TOPSIS in solving complex decision-making problems. However, there is no relevant research combining fuzzy AHP method with fuzzy evidence reasoning (FER) and TOPSIS, especially for failure assessment in FMEA, and FER is well-suited for handling incomplete assessment of uncertainty.

For determining the weights of risk factors, the available literature provides details for methods such as AHP [21], fuzzy AHP [22,23], and analytic network process (ANP) [24]. Kutlu and Ekmekçioğlu [7] introduced the fuzzy theory into FMEA analysis and used the fuzzy analytic hierarchy process to determine the weight of risk factors, but ignored the objective information of risk factors themselves. AHP was used to derive the relative priorities of evaluation criteria in the FTOPSIS approach to rank failure modes by Carpitella et al. [23]. Boral et al. [25] used Buckley's fuzzy AHP method to calculate the fuzzy weights of the risk factors. Li and Hao [26] used an example to verify the variable weight effect of variable weight vector in the comprehensive decision-making. To weigh the risk factors, Liu et al. [22] integrated the fuzzy analytic hierarchy process (AHP) and the entropy method. Rezaei [27] proposed best-worst method (BWM) to determine the importance weights of criteria, flexibly. This approach is a comparison-based method that establishes the comparisons between items in a particular way. The traditional BWM uses crisp values to conduct the comparisons so it fails to determine weights under uncertain environment. Thus, to obtain the weights of risk factors, fuzzy BWM [28–30] is employed. However, BWM involves tedious processes and a few pair-wise comparisons to achieve consistent results. Moreover, in some FMEA models, the weights of FMEA team members are assumed to be known or equal; such an approach cannot avoid subjective randomness.

The current study proposes an integrated approach for FMEA. In the proposed framework, using the fuzzy evidence reasoning method, the ratings of O, S, and D are represented in fuzzy belief-structures to express the diverse and the uncertain. To determine the weights of O, S, and D, the subjective experience of the experts and the objective information of the ratings are considered comprehensively. The variable-weight method and entropy-weight method are used to calculate the weights reflected by the objective information. Additionally, the objective and the subjective weights are combined and integrated to obtain the comprehensive weight of O, S, and D. To prioritize the risk of potential failure modes, the fuzzy TOPSIS method is adopted.

The rest of the paper is organized as follows: FPSO oil and gas processing system is introduced in Section 2. The proposed methodology is described in Section 3. Risk identification of FPSO oil and gas processing system is offered in Section 4, and the analysis of results is made in Section 5. Section 6 gives the conclusions of this paper.

2. FPSO Oil and Gas Processing System

As the most important component of the FPSO upper module, the FPSO oil and gas processing system roughly resembles its on-shore contemporaries, including oil-gas-water separation, associated gas processing, electric dehydration and desalination, production sewage processing, crude oil external measurement, chemical injection, heating medium, torch-venting systems, etc. The processing technology flow diagram of FPSO oil and gas processing system is shown in Figure 1.

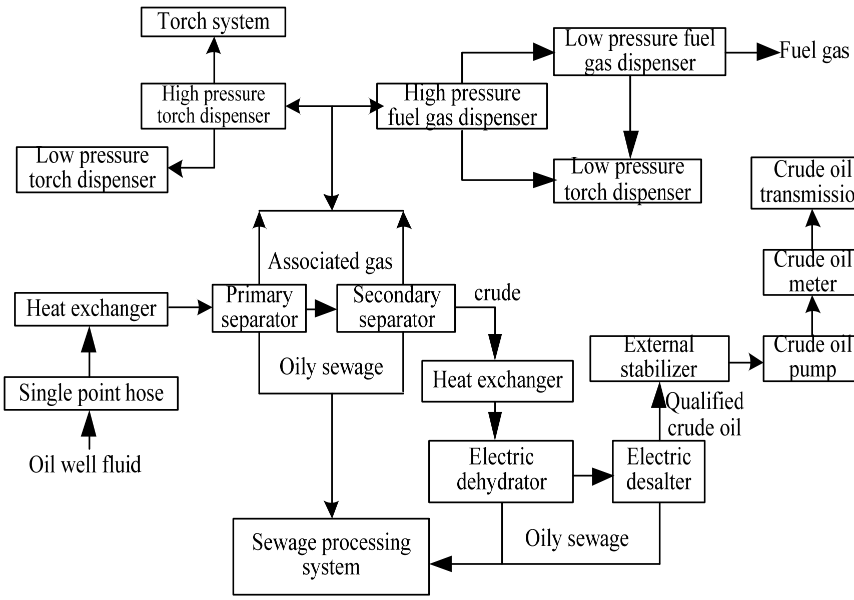

Figure 1. The processing technology flow diagram of floating production storage and offloading system (FPSO) oil and gas processing system.

The submarine oil-well produces fluid by a single-point hose, which is heated to a certain temperature by a crude oil heat exchanger before it enters a primary (high-pressure) separator. There, with the addition of chemicals, the separation of oil, gas, and water can be initially realized. The separated gas is sent to the associated gas-processing system, and the separated oily sewage enters the production sewage treatment system. The crude oil that is separated is heated to a certain temperature by the heat exchanger and the crude oil heater, and then enters the high-pressure separator for secondary separation. The gas generated after the second separation enters the associated gas processing system; the sewage enters the production sewage processing system; and the crude oil, after the secondary separation treatment, enters the tertiary separator again for separation. The crude oil is buffered, stabilized, and decompressed in the vessel after three separations, then heated and transported to the electric dehydration and desalination system to remove impurities such as emulsified water and inorganic salts in crude oil, to finally obtain relatively pure crude oil. The pure crude oil is sent to be measured at the crude oil external measurement system. After that, it is transported to the cargo tank of the FPSO for storage. The gas generated in the above process is uniformly transported to the associated gas processing system for separation, dehydration, decontamination, and purification, before the natural gas can be obtained. The purified natural gas can then be used as fuel for the FPSO itself, and the excess can be injected into the oil field or to the torch to vent or burn. The sewage generated in the process is collected in the production sewage processing system for filtration, sedimentation, oil-water separation, and other processes. The purified sewage can be directly discharged or can be injected back into the oil and gas field, while the non-standard sewage will be processed again until it is purified and then discharged into the sea.

3. The Proposed Approach

In this section, to prioritize the potential failure modes, a risk identification approach based on a fuzzy TOPSIS integrated fuzzy evidential reasoning approach is proposed.

Fuzzy logic is a tool that transforms the vagueness of human feelings and recognitions, and their decision-making ability into a mathematical formula. It also provides a meaningful representation of measurement for uncertainties and vague concepts expressed in natural language. So, a fuzzy multi-criteria decision-making method is preferred instead of crisp decision-making methods for overcoming the conventional FMEA shortcomings.

Based on fuzzy evidence reasoning and comprehensive weighting method, the fuzzy TOPSIS is improved. In view of the diversity and uncertainty of O, S, and D ratings, the method uses fuzzy evidence reasoning to express the ratings of O, S, and D in a fuzzy belief structure. In order to take the objective information contained in the O, S, and D ratings into account, the O, S, and D subjective and the objective weights are combined and weighted by a comprehensive weighting method. In determining the comprehensive weight, two methods are proposed: subjective-entropy integrated weight method and subjective-variable integrated weight method. Last, fuzzy TOPSIS is utilized to obtain the closeness coefficients of processes, according to which, the ranking order of all failure modes is determined.

All necessary steps required for making a risk prioritization assessment using the proposed approach are outlined in Figure 2. The step-details of the proposed methodology is discussed as follows:

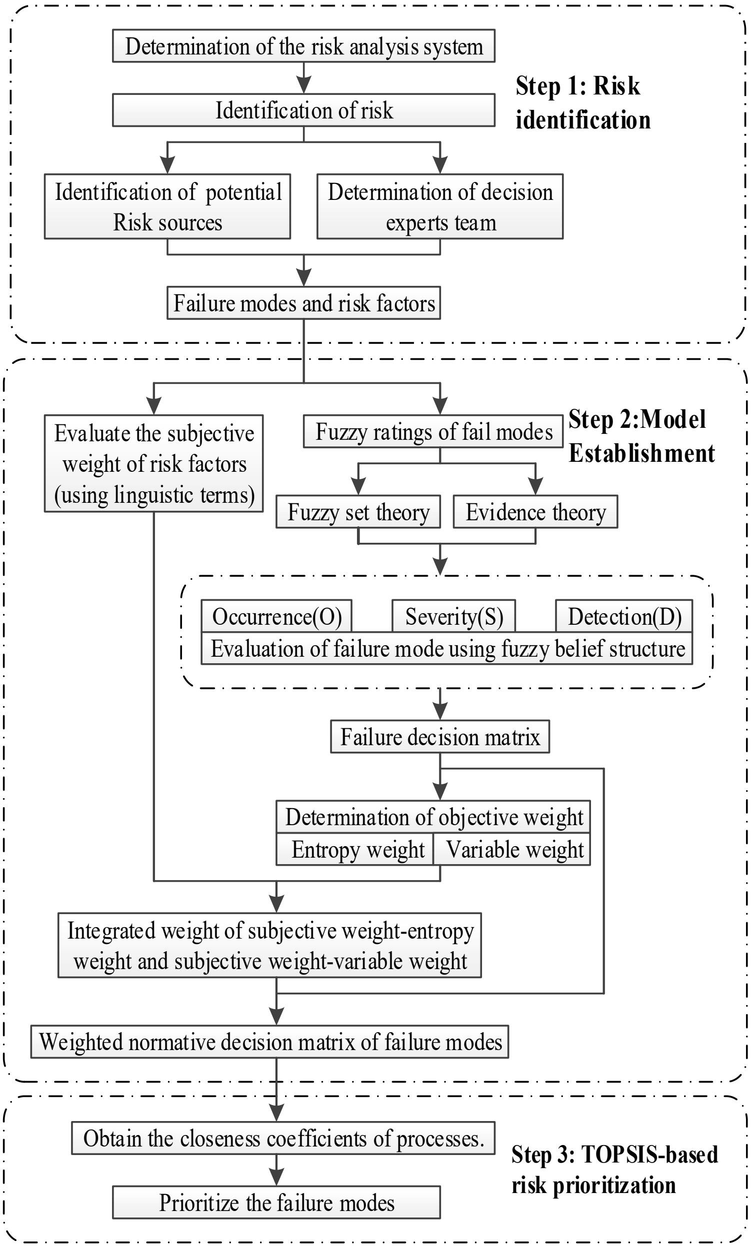

Figure 2. Flowchart of the proposed approach.

3.1. Risk Identification (Step 1)

In this step, the decision expert team should be determined first. Suppose there are K experts to make decisions (DE_1, $DE_2, \cdots, DE_K$) in an FMEA team that is responsible for the assessment. Different experts may have different knowledge, experience, and individual preferences, so they will express various views and subjective perceptions on the same failure modes. Therefore, each decision expert DE_k is given a weight $\lambda_k > 0$ $(k = 1, \cdots, K)$ satisfying $\sum_k^K \lambda_k = 1$ to reflect his/her relative importance in the FMEA team. Expert weights should be determined by direct rating, point allocation, the eigenvector method, linear programming techniques for multi-dimension analysis of preferences (LINMAP), the Delphi method, etc. In this paper, expert weight can be calculated by Equation (1). If there is not enough reason or evidence to show the differences among the FMEA team in their judgment qualities, the team experts should be given equal weight.

$$\lambda_k = \frac{H_k}{\sum_{k=1}^{K} H_k} \quad (1)$$

where: H_k is the score of the expert DE_k, given in Table 1.

Table 1. Weight allocation table of expert weight.

Aspects	Classes	Scores
Qualification	Senior expert	5
	Senior designer or operator	4
	Intermediate designer or operator	3
	General technician	2
	General operator	1
Work experience	More than 30 years	5
	20–29 years	4
	10–19 years	3
	5–9 years	2
	Less than 5 years	1
Field familiarity	very familiar	5
	familiar	3

Then potential leak sources of oil and gas leakage related to FPSO oil and gas processing system should be identified.

3.2. Model Establishment (Step 2)

The purpose of Step 2 is to develop a quantitative assessment of risk factors related to each failure mode, which is the core procedure of the proposed approach. This step can be divided into four sub-steps.

(a) Establishment of Group fuzzy belief structures combining fuzzy logic;
(b) Determination of subjective weight;
(c) Determination of two kinds of comprehensive weighting methods;
(d) Establishment of weighted normalized decision matrix.

3.2.1. Establishment of Group Fuzzy Belief Structures Combining Fuzzy Logic (Sub-Step 1)

As a result of diverse and uncertain characteristics of subjective judgments, evidential reasoning (ER) theory, integrated with fuzzy set theory, is used to express experts' judgments. The main advantage of the ER approach is that both precise data and subjective judgments with uncertainty can be consistently modeled under the unified framework [31]. The ratings of O, S, and D are expressed in an individual evaluation grade set that is defined as a fuzzy set H as follows:

$$H = \{H_{11}, H_{22}, H_{33}, H_{44}, H_{55}\} = \{VeryLow, Low, Moderate, High, VeryHigh\}$$

Based on experts' opinions, we can approximate all the five individual assessment grades by using fuzzy numbers. Trapezoidal fuzzy number is mainly used to solve the problem of membership degree, and the fuzziness and uncertainty of evaluation can be expressed in the form of interval, which is consistent with the reason of using trapezoidal fuzzy number in this paper. Therefore, linguistic variables are approximated as trapezoidal fuzzy numbers [32]. Their membership function values can be determined according to the historical data and the detailed questionnaire answered by all experts, as shown in Figure 3 and Table 2.

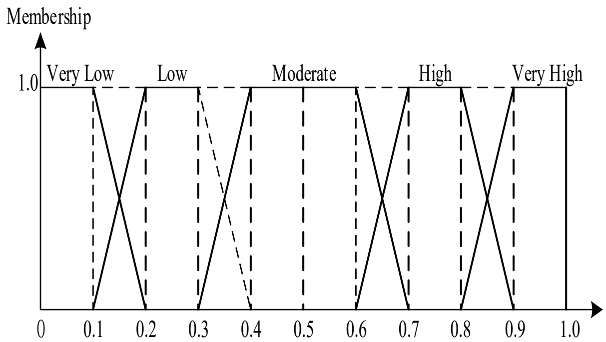

Figure 3. Fuzzy membership function for linguistic terms.

Table 2. Fuzzy ratings for linguistic terms of risk factors.

Linguistic Terms	Assessment Criteria			Trapezoidal Fuzzy Number
	Occurrence(O)	Severity(S)	Detect Ability(D)	
Very Low (VL)	Failure mode is extremely unlikely to happen	The failure mode has no effect on the system function, and the operator may not notice the failure.	The defect still exists until the system function fails to complete the established task to some extent.	(0,0,0.1,0.2)
Low(L)	May happen once, but it cannot happen again or happen often	Failure has a slight impact on the operator but does not continue to affect the system	Defects still exist until system performance is severely degraded	(0.1,0.2,0.3,0.4)
Moderate(M)	May happen again	Failure causes the operator to be highly uncomfortable or has a slight impact on system function and can be perceived by the operator	Defects still exist until system functionality is affected	(0.3,0.4,0.6,0.7)
High(H)	Almost happen at least once	Failure causes serious problems on the system function and may result in minor personal injury	Defects still exist until observation or testing	(0.6,0.7,0.8,0.9)
Very High (VH)	Almost happen several times	Failure causes system function to be greatly affected, which may cause casualties	Failure cannot be detected, and defects can be detected.	(0.8,0.9,1.0,1.0)

Furthermore, we define the interval fuzzy assessment grade sets H_{ij} for $i = 1 - 4$ and $j = i + 1$ to 5 as trapezoidal fuzzy sets that include fuzzy individual grades H_{ii}, $H_{(i+1)(i+1)}$, H_{jj}.

The assessment grades in the FMEA may represent a vague concept, and there may be no clear distinctions between the meanings of two adjacent grades. In other words, these evaluation grades may not be regarded as crisp sets. Such a problem can be solved by the FER approach, which allows FMEA decision experts to provide their subjective judgments flexibly: the assessment grades for each failure mode is expressed as $\left\{ \left(H_{ij}, U_{ij}^{k}(FM_n, V_{Fl}) \right),\ i \leq j,\ i,\ j = 1, \cdots, 5, n = 1, \ldots\ldots, \ N, l = 1,\ 2,\ 3. \right\}$ when l = 1, 2, 3, means O, S, and D, respectively. Where $U_{ij}^{k}(FM_n, V_{Fl})$ is the confidence of the kth expert on the fuzzy grade H_{ij}. If $\sum_{i=1}^{5} \sum_{j=1}^{5} U_{ij}^{k}(FM_n, V_{Fl}) = 1$, that is, the confidences (also called belief degrees) of the kth expert in his/her subjective judgments are summed to one, then the assessment is said to be complete; otherwise, it is said to be an incomplete assessment, where the missing information is referred to as local ignorance and could be assigned to any grade between Very Low and Very High. In particular, if the decision expert is not willing to, or cannot provide an assessment for a failure mode with respect to the risk factor under consideration, the assessment can be expressed as {(H15,1.0)}. Such judgments are referred to as total ignorance. Obviously, the belief structures in the FER approach provide FMEA decision experts with an easy-to-use and very flexible way to express their opinions, and can better quantify risk factors than the traditional RPN methodology.

The collective assessment of the K decision experts for each failure mode with respect to each risk factor is also a belief structure, called group or collective belief structure, which is denoted as:

$$U_{ij}(FM_n, V_{Fl}) = \sum_{k=1}^{K} \lambda_k U_{ij}^k(FM_n, V_{Fl}), \tag{2}$$

$$\overline{x}_n(l) = \sum_{i=1}^{5} \sum_{j=1}^{5} H_{ij} U_{ij}(FM_n, V_{Fl}), \tag{3}$$

where $\overline{x}_n(l)$, $n = 1, 2, \cdots, N$, $l = \mathrm{O, S, D}$, is a fuzzy number. For comparison or ranking purposes, fuzzy numbers often need to be defuzzified to crisp numbers. The most extensively used defuzzification approach is the centroid defuzzification [33]. So, the crisp values of $\overline{x}_n(l)$ is denoted as $x_n(l)$ by defuzzification. So, the group belief structures for the N failure modes with respect to the risk factors O, S, D form a fuzzy belief decision matrix are shown in Equation (4).

$$X = \begin{array}{c} \\ FM_1 \\ FM_2 \\ \vdots \\ FM_N \end{array} \begin{array}{c} \begin{array}{ccc} O & S & D \end{array} \\ \begin{bmatrix} x_1(1) & x_1(2) & x_1(3) \\ x_2(1) & x_2(2) & x_2(3) \\ \vdots & \vdots & \vdots \\ x_N(1) & x_N(2) & x_N(3) \end{bmatrix} \end{array}, \tag{4}$$

3.2.2. Determination of Subjective Weight (Sub-Step2)

Since it is difficult to determine the O, S, and D weights, they are also expressed in fuzzy linguistic terms by each decision expert. The triangular fuzzy number is mainly used to solve multi-decision problems and is used to solve the weight value of factors. Therefore, triangular fuzzy numbers are used to represent linguistic terms in this paper, as shown in Table 3. Figure 4 shows the membership function for the sake of visualization.

Table 3. Fuzzy linguistic weights for the relative importance of risk factors.

Linguistic Variable	Triangular Fuzzy Number
Very Unimportant (VUI)	(0,0,0.25)
Unimportant (UI)	(0,0.25,0.5)
Medium Important (MI)	(0.25,0.5,0.75)
Strong Important (SI)	(0.5,0.75,1)
Very Strong Important (VSI)	(0.75,1,1)

Assume that the decision expert $DE_K's$ subjective weight rating for O, S, and D for a failure mode is expressed as $\left(\omega_{lO}^k, \omega_{lS}^k, \omega_{lD}^k\right)$, then, by integrating all the decision experts' weight of the same risk factor, the weight can be expressed as:

$$\omega_l^S = \left(\sum_{k=1}^{K} \lambda_k \omega_{lO}^k, \sum_{k=1}^{K} \lambda_k \omega_{lS}^k, \sum_{k=1}^{K} \lambda_k \omega_{lD}^k\right), \tag{5}$$

The language rating in the weight is defuzzified using centroid defuzzification method, and the subjective weights of O, S, and D can be normalized using the following equation:

$$\overline{\omega_l^S} = \frac{\omega_l^S}{\sum_{l=1}^{K} \omega_l^S}, \tag{6}$$

where $\overline{\omega_l^S}$ is the subjective weight obtained after normalization of ω_l^S.

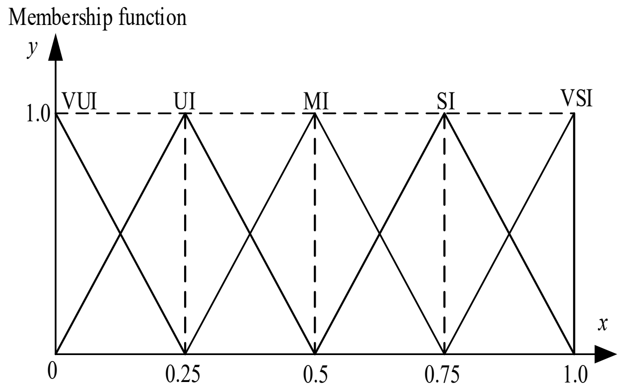

Figure 4. Membership functions for rating risk factor weights.

3.2.3. Determination of Two Kinds of Comprehensive Weighting Methods (Sub-Step 3)

The final decision in the case of multi-attributive and multi-objective decision-making problems is influenced by factors such as indicator characteristics and decision preferences. Although the weight determination methods of these factors are diverse, the selection of different methods is directly related to the accuracy and rationality of the final decision results. In general, the weight determination method can be divided into subjective, objective, and comprehensive weighting method. The subjective weighting method determines the relative weight of evaluation indicators through the subjective experience of analysts. This analytical method is too biased toward the preferences and experiences of decision-makers, mainly including AHP and the Delphi method (the expert investigation method). The objective weighting method is based on the information contained in the obtained index data to determine the weight but does not consider the subjective information such as the experience of the decision expert. The comprehensive weighting method, which integrated the indicator information and the decision-maker's subjective experience, gives more realistic results.

Two kinds of comprehensive weighting methods, namely the subjective-entropy integrated weight method and the subjective-variable integrated weight method, are developed.

(a) Subjective-entropy integrated weight method

The main idea of this method is to use the information entropy to calculate the entropy weight of each risk factor. The size of the information entropy reflects the degree of disorder. The smaller the information entropy, the lower the degree of disorder, and the greater the utility value, so the weight is larger. In the matrix obtained after defuzzification, the entropy of the l-th risk factor is:

$$E_l = -\frac{1}{ln(N)}\sum_{n=1}^{K}(x_n(l)ln(x_n(l))), \tag{7}$$

where $n = 1, 2, \cdots N$, $l = 1, 2, 3$, so the entropy weight of each risk factor is:

$$\omega_l^E = \frac{1 - E_l}{\sum_{l=1}^{3}(1 - E_l)}, \tag{8}$$

The multiplicative combination weighting method is adopted. Subjective weight determined based on expert experience and entropy weight is comprehensively weighted. $\overline{\omega_l^S}$ is the subjective weight. That is, the subjective-entropy integrated weight is as follows:

$$\omega_l^{SE} = \frac{\omega_l^E\overline{\omega_l^S}}{\sum_{l=1}^{3}\omega_l^E\overline{\omega_l^S}}, \tag{9}$$

(b) Subjective-variable integrated weight method

Variable weight is adjusted based on the subjective weight of the risk factor, and subjective weight is usually obtained through the subjective experience of the decision-experts. The weight obtained by the variable weight method combines the subjective experience of the decision-makers with the objective values of the factors, so the results obtained are more scientific and reasonable.

First, the variable weight vector must be constructed. Here, the exponential state variable weight vector selected due to the parameter setting is convenient, and the decision requirements are obvious. A set of state vector functions based on the "incentive" or "punish" variable weight mechanism is constructed so that the weight value can reflect the influence of the value of each indicator on the decision result. Since the risk factors O, S, and D are cost-type variables, that is, the smaller the risk factor value, the better. so the larger state values should be given greater weight, which will attract the attention of decision-makers.

A state vector for the failure mode is constructed as follows:

$$S(x_n(l)) = \mathrm{e}^{\alpha(x_n(l)-\overline{x_n})}, \tag{10}$$

$$\overline{x_n} = \sum\nolimits_{l=1}^{3} x_n(l)/3, \tag{11}$$

where $x_n(l)$ is the l-th risk factor rating of the nth failure mode; $S(x_n(l))$ is the variable weight vector corresponding to $x_n(l)$. $\overline{x_n}$ is the arithmetic mean of $x_n(l)$, l = 1, 2, 3; the constant α is any real number.

The level of decision-making requirements for the balance of the risk factor is reflected by the constant, α. When it takes a positive number and is larger, the corresponding state value is considered more when making the decision; that is, it will be given greater weight. The state vector at this time is called an excitation variable weight vector. When the negative value is taken, and it is smaller, the corresponding state value is considered less, that is, the weight is smaller, and the result is preferably a more balanced state vector of the risk factor. The state vector at this time is called a penalty variable weight vector.

The variable weight and the subjective weight determined are comprehensively integrated:

$$\omega_l^{SV}(x_n(l)) = \frac{\overline{\omega_l^S}\mathrm{S}(x_n(l))}{\sum_{n=1}^{N}\left(\overline{\omega_l^S}\mathrm{S}(x_n(l))\right)}, \tag{12}$$

where $\omega_l^{SV}(x_n(l))$ is the subjective-variable integrated weight, $n = 1,2,\cdots N, l = 1,2,3$.

3.2.4. Establishment of Weighted Normalized Decision Matrix (Sub-Step4)

The defuzzified matrix is obtained according to Equation (4). The comprehensive weight is obtained from Equation (9) or (12), so the weighted normalization matrix can be obtained by multiplication:

$$\mathrm{V} = [v_{nl}]_{N\times 3}, \tag{13}$$

where $v_{nl} = x_n(l)\cdot\omega_l^{SE}$ or $v_{nl} = x_n(l)\cdot\omega_l^{SV}(x_n(l))$, $n = 1,2,\cdots,N, l = O, S, D$.

3.3. Topsis-Based Risk Prioritization (Step3)

TOPSIS, which is one of the classical multi-criteria decision-making methods, was developed by Hwang and Yoon (1981). According to the weighted normalized fuzzy decision matrix, we know that the elements $v_{nl}\forall n,\ l$ are normalized positive numbers, and their ranges belong to the closed interval [0, 1]. Then, we can define the positive-ideal solution A^+ and negative-ideal solution A^- as

$$\mathrm{A}^+ = (1,1,1), \tag{14}$$

$$\mathrm{A}^- = (0,0,0) \tag{15}$$

The distance of each failure mode from A^+ and A^- can be currently calculated as

$$d_n^+ = \sqrt{\sum_{l=1}^{3} (v_{nl} - 1)^2}, \quad (16)$$

$$d_n^- = \sqrt{\sum_{l=1}^{3} (v_{nl} - 0)^2} \quad (17)$$

where d_n^+ is the Euclidean distance from the failure mode FM_n to the positive-ideal solution; d_n^- is the Euclidean distance from the failure mode FM_n to the negative-ideal solution.

The closeness coefficient of each failure mode C_n can be calculated as follows:

$$C_n = \frac{d_n^-}{d_n^+ + d_n^-}, \ n = 1, 2, \cdots, N, \quad (18)$$

Obviously, a failure mode FM_n is closer to A^+ and farther from A^- as C_n approaches to 1. Therefore, according to the closeness coefficient, we can determine the ranking order of all failure modes.

4. Risk Identification of FPSO Oil and Gas Processing System Leakage

Taking the 150,000-ton "OFFSHORE-111" FPSO as the study subject, this module is classified to simplify the FMEA analysis of the FPSO leakage risk. The International and European Standard IEC EN 60079–10–2 "Classification of areas–explosive gas atmospheres" pointed out that hazardous areas shall be classified in zones based on the frequency of occurrence and persistence of the dangerous atmosphere, as reported in Table 4.

Table 4. Zone types.

Zones	Characteristics
Zone 0	An explosive atmosphere is present continuously or for long periods or frequently
Zone 1	An explosive atmosphere is likely to occur in normal operation occasionally
Zone 2	An explosive atmosphere is not likely to occur in normal operation but, if it does occur, will persist for a short period only

The oil and gas processing module includes equipment and facilities, such as oil and gas storage tanks, transfer devices, protected fire containers, etc. Due to the high concentration and release of explosive gas, this area should be classified as Zone 0. There are 12 main failure modes in total, which were identified by an FMEA team and are presented together with their causes and effects on the systems in Table 5.

The FMEA team consists of five cross-functional experts. The selection of experts and their weight distribution have a significant impact on the accuracy and stability of the evaluation results. In this research, the experts fulfill three significant criteria: (1) have more than ten years' experience in FPSO design, building, and inspection; (2) still working in the offshore engineering industry; and (3) have high-level knowledge of and experience in FPSO systems. Keeping in mind the above criteria, the expert team, which consists of one professor of Harbin Engineering University with a major in offshore oil and gas security, one senior chief engineer of China National Offshore Oil Corporation (CNOOC), one senior designer of China International Marine Containers (CIMC Raffles), one senior designer engaged in marine engineering design in a university, and one platform engineer of China National Offshore Oil Corporation (CNOOC). Different scores and weights are given to team experts, as shown in Table 6.

Table 5. Failure mode and effect analysis (FMEA) for FPSO oil and gas processing system.

ITEM	Component	Failure Mode	Cause of Failure	Failure Effect
1	Primary separator	Natural gas leakage	Corrosion, fatigue crack, quality defects	Equipment damage, Discontinuation repair, Casualties
2	Secondary separator	Natural gas leakage	Corrosion, fatigue crack, quality defects	Equipment damage, Discontinuation repair, Casualties
3	Crude oil measurement	Crude oil leakage	Corrosion, suddenly strike, maloperation	Equipment damage, Discontinuation repair, Casualties
4	Electric dehydration	Crude oil leakage	Suddenly strike, maloperation, fatigue crack	Equipment damage, Discontinuation repair, Casualties
5	Crude oil flash tank	Crude oil leakage	Corrosion, abrasion, fatigue crack	Equipment damage, Discontinuation repair, Casualties
6	Secondary heater	Crude oil leakage	Corrosion, suddenly strike, maloperation	Equipment damage, Discontinuation repair, Casualties
7	Crude oil cooler	Crude oil leakage	Corrosion, suddenly strike, fatigue crack	Equipment damage, Discontinuation repair, Casualties
8	Crude oil heat exchanger	Crude oil leakage	Corrosion, maloperation, fatigue crack	Equipment damage, Discontinuation repair, Casualties
9	Fuel gas scrubber	Natural gas leakage	Suddenly strike, material defect, fatigue crack	Equipment damage, Discontinuation repair, Casualties
10	Fuel gas cooler	Natural gas leakage	Suddenly strike, material defect, fatigue crack	Equipment damage, Discontinuation repair, Casualties
11	Crude oil separator	Crude oil leakage	Corrosion, suddenly strike, fatigue crack	Equipment damage, Discontinuation repair, Casualties
12	Fuel oil filter	Fuel oil leakage	Corrosion, suddenly strike, fatigue crack	Equipment damage, Discontinuation repair, Casualties

Table 6. Determination of expert weight.

Decision Experts	Qualification	Work Experience	Field Familiarity	Scores	Weight
DE1	5 (Senior expert)	5 (More than 30 years)	5 (Very familiar)	125	0.35
DE2	5 (Senior expert)	5 (More than 30 years)	3 (Familiar)	75	0.2
DE3	4 (Senior designer or operator)	3 (10–19 years)	5 (Very familiar)	60	0.15
DE4	4 (Senior designer or operator)	4 (20–29 years)	5 (Very familiar)	80	0.2
DE5	3 (Intermediate designer or operator)	4 (20–29 years)	3 (Familiar)	36	0.1

The FMEA team functions to prioritize these 12 failure modes in terms of their failure risks, such as the probability of occurrence, severity, and detectability, so that high-risk failure modes are corrected with top priority. Due to the difficulty in precisely assessing the risk factors and their relative weight importance, the team members agree to evaluate them using the linguistic terms that are defined in Tables 2 and 3. The assessment information of the 12 failure modes on each risk factor and the risk factor weights provided by the five decision experts are presented in Table 7, where incomplete assessments and ignorance information are shaded and highlighted.

The data from the FMEA in Table 7 are analyzed using Equations (2) and (3), and the crisp values of these 12 failure modes, O, S, and D factors, are obtained by using centroid defuzzification, as shown in Figure 5.

Subjective-entropy integrated weight ω_l^{SE} is obtained by using Equations (7)–(9), that is, 0.383, 0.334, and 0.283. The risk factors O, S, and D are cost-type variables, that is, the smaller these values, the better the risk evaluation. Therefore, when constructing a state-type variable weight vector, a larger state value should be given a greater weight, which can attract the attention of the decision-makers. The excitation variable weight vector is selected, that is, α is a positive number, but its specific value can be analyzed by sorting the result, and $\alpha = 1$ is temporarily taken.

Table 7. Assessment information on 12 failure modes by five FMEA experts.

Risk Factors	FMEA Experts	Factors Weights	FM1	FM2	FM3	FM4	FM5	FM6
Occurrence	DE1(0.35)	VSI	H33	H33,0.5 H44,0.5	H22	H12,0.9	H23,0.5	H22,0.9 H33,0.1
	DE2(0.20)	MI	H44	H23	H22	H22	H12	H34,0.8
	DE3(0.15)	SI		H33	H23	H12,0.9	H13	
	DE4(0.20)	SI	H34	H23	H33	H12	H23,0.5	H33
	DE5(0.10)	MI	H25	H22	H22	H22	H22,0.9	H34,0.7 H33,0.2
Severity	DE1(0.35)	MI	H35,0.9	H45,0.9	H34	H44	H34	H34
	DE2(0.20)	VSI	H55	H45	H33	H33	H33	H35
	DE3(0.15)	SI	H45	H34	H45	H33,0.9	H23,0.5	H34
	DE4(0.20)	SI	H55	H44	H33	H33	H44	H35
	DE5(0.10)	VSI	H44	H45	H44	H34	H33	H44
Detectability	DE1(0.35)	SI	H33	H33	H22	H23	H22	H23
	DE2(0.20)	UI	H34	H44,0.9	H22	H23	H22	H22
	DE3(0.15)	MI	H33	H24	H23	H12,0.8	H23	H22
	DE4(0.20)	UI	H22	H34	H22	H33		H12
	DE5(0.10)	UI	H23	H33,0.9	H24	H22	H14	H12
Risk factors	FMEA experts	Factors weights	FM7	FM8	FM9	FM10	FM11	FM12
Occurrence	DE1(0.35)	VSI	H22	H22,0.9	H33	H22,0.7 H33,0.3	H33,0.5	H22
	DE2(0.20)	MI	H33	H23	H34	H22	H33	H23
	DE3(0.15)	SI	H33,0.9	H33	H23	H33	H33	H23
	DE4(0.20)	SI	H34	H34	H33	H33	H34	H22
	DE5(0.10)	MI	H22	H22	H33	H23	H34	H12
Severity	DE1(0.35)	MI	H22,0.4 H33,0.5	H23	H45	H34	H33	H22
	DE2(0.20)	VSI	H44	H33	H44	H33	H34	H13
	DE3(0.15)	SI	H44	H34	H33,0.2 H44,0.6	H33	H33	H22
	DE4(0.20)	SI	H34	H23	H44	H44	H44	H23
	DE5(0.10)	VSI	H44	H33	H44	H34	H34	H22
Detectability	DE1(0.35)	SI	H23	H23	H33	H33	H33	H33
	DE2(0.20)	UI	H33,0.9	H22	H23,0.8	H23	H33	H23
	DE3(0.15)	MI	H22	H23	H33	H22	H22	H33
	DE4(0.20)	UI	H22	H22	H23		H23	H33
	DE5(0.10)	UI	H22	H12	H33	H22	H33	H24

Variable weight state vector for each failure mode $S(x_n(l))$ and subjective-variable integrated weight $\omega_l^{SV}(x_n(l))^{\alpha=1}$ can be obtained from Equations (10)–(12), as shown in Table 8.

Table 8. Variable weight state vector and subjective-variable integrated weight for 12 failure modes.

	Variable Weight State Vector (α = 1)			Subjective-Variable Integrated Weight		
Failure Modes	**Occurrence**	**Severity**	**Detect-Ability**	**Occurrence**	**Severity**	**Detect Ability**
FM_1	1.190	1.280	1.063	0.109	0.083	0.067
FM_2	0.877	1.215	1.380	0.080	0.079	0.088
FM_3	0.943	1.333	1.223	0.086	0.087	0.078
FM_4	0.785	1.287	1.416	0.072	0.084	0.090
FM_5	0.768	1.323	1.375	0.070	0.086	0.087
FM_6	0.843	1.400	1.275	0.077	0.091	0.081
FM_7	0.923	1.216	1.229	0.085	0.079	0.078
FM_8	0.962	1.204	1.244	0.088	0.079	0.079
FM_9	0.967	1.444	1.304	0.089	0.094	0.083
FM_{10}	0.835	1.302	1.433	0.077	0.085	0.091
FM_{11}	0.896	1.282	1.405	0.082	0.084	0.089
FM_{12}	0.926	1.048	1.412	0.085	0.068	0.090

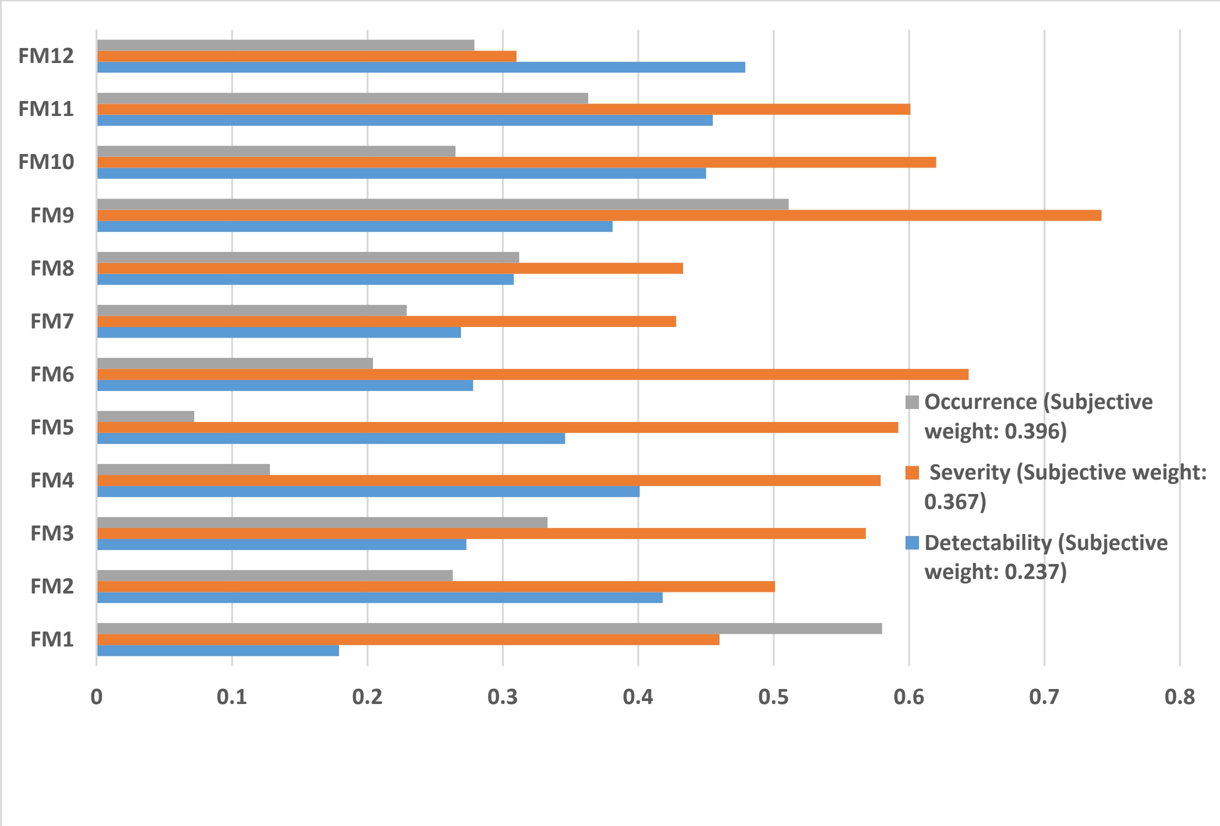

Figure 5. Defuzzified crisp values for 12 failure modes.

The weighted normalization matrix is calculated by Equation (13), and then, based on the TOPSIS method, Euclidean distance to the positive-ideal solution d_n^+, Euclidean distance to the negative-ideal solution d_n^- and the closeness coefficient C_n of all failure modes can be obtained by Equations (14)–(18). Finally, as shown in Table 9, the scores are ranked, and results show that the most important failure mode is "Fuel gas scrubber" (FM9).

Table 9. Ranking of failure modes using the improved fuzzy Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) approach.

	Improved Fuzzy TOPSIS (Subjective-Variable Integrated Weight Method)				Improved Fuzzy TOPSIS (Subjective-Entropy Integrated Weight Method)			
Failure Modes	d_n^+	d_n^-	C_n	**Ranking**	d_n^+	d_n^-	C_n	**Ranking**
FM_1	1.667	0.075	0.043	2	1.491	0.275	0.156	3
FM_2	1.676	0.058	0.033	9	1.510	0.228	0.130	8
FM_3	1.675	0.061	0.036	6	1.506	0.241	0.138	5
FM_4	1.678	0.061	0.035	7	1.530	0.230	0.131	7
FM_5	1.683	0.060	0.034	8	1.550	0.222	0.126	9
FM_6	1.676	0.065	0.037	5	1.521	0.242	0.137	6
FM_7	1.689	0.044	0.026	12	1.556	0.184	0.106	12
FM_8	1.683	0.050	0.029	11	1.530	0.207	0.119	10
FM_9	1.648	0.089	0.051	1	1.417	0.334	0.191	1
FM_{10}	1.666	0.070	0.040	4	1.482	0.264	0.151	4
FM_{11}	1.662	0.071	0.041	3	1.463	0.276	0.159	2
FM_{12}	1.682	0.053	0.031	10	1.533	0.201	0.116	11

5. Discussion

The results obtained for the FMEA using the proposed approach are collated with the results obtained from the fuzzy TOPSIS and are given in Table 10.

As different methods were adopted to obtain the relative closeness, and used to reflect the risk priority of the failure mode, the relative closeness is quite different. Therefore, it is not necessary to carry out a horizontal comparison because the focus is on the risk prioritization of failure modes.

Table 10. Ranking Comparison.

	Improved Fuzzy TOPSIS				Fuzzy TOPSIS	
	Subjective-Variable Integrated Weight Method		Subjective-Entropy Integrated Weight Method			
Failure Modes	C_n	**Ranking**	C_n	**Ranking**	C_n	**Ranking**
FM_1	0.043	2	0.156	3	0.163	3
FM_2	0.033	9	0.130	8	0.134	8
FM_3	0.036	6	0.138	5	0.145	6
FM_4	0.035	7	0.131	7	0.135	7
FM_5	0.034	8	0.126	9	0.131	9
FM_6	0.037	5	0.137	6	0.146	5
FM_7	0.026	12	0.106	12	0.110	12
FM_8	0.029	11	0.119	10	0.123	10
FM_9	0.051	1	0.191	1	0.199	1
FM_{10}	0.040	4	0.151	4	0.155	4
FM_{11}	0.041	3	0.159	2	0.163	2
FM_{12}	0.031	10	0.116	11	0.112	11

Comparing the results of improved fuzzy TOPSIS and fuzzy TOPSIS, it is found that the risk priority of each failure mode is basically the same. The failure modes with a higher risk priority are FM9, FM1, and FM11, but there are minor differences (such as in FM1 and FM11). The main reasons for this difference are: (1) the improved fuzzy TOPSIS expresses the uncertainty, diversity, and absence of O, S, and D ratings in a comprehensive fuzzy confidence structure, while fuzzy TOPSIS simply approximates these problems in rating; (2) the improved fuzzy TOPSIS uses comprehensive weighting method (the subjective-variable integrated weight method and subjective-entropy integrated weight) to make full use of O, S, and D rating information, while fuzzy TOPSIS only considers subjective weights, ignoring the objective information of O, S, and D ratings.

When determining the objective weights of O, S, and D, the entropy weight method adjusts the weight of O (S or D) of any failure mode in the value of O (S or D) in all failure modes. The variable weight method adjusts the weight according to the ratings of O, S, and D in the same failure mode. In order to observe the variable weight effect when α takes different values, those values are analyzed. The sorting results of the variable weight method are shown in Table 11 and Figure 6, when α takes different values.

From Table 11 and Figure 6, it is seen that as α increases, the priority order of some failure modes changes. For example, FM_1 and FM_6 rank up, while FM_9 and FM_{11} rank down. These changes are closely related to changes in the weights of O, S, and D. For example, the O, S, and D values of FM_1 are 0.580, 0.460, and 0.179, respectively, and the subjective weights are 0.396, 0.367, and 0.237; whereas the O value is relatively large and the subjective weight is also large. After the variable weight processing, along with α's increase, the risk factor of O value in the comprehensive weight increases continuously, and the risk of O value is amplified. Therefore, FM_1 sorting rises.

The equipment of the oil and gas processing system selected in this analysis is closely related to the oil and gas processing process, so the failure of any risk factor will cause a series of chain reactions. If the value of α is larger, then the consequences of the high-value risk factor and the resulting consequences will also be magnified. Therefore, it is more necessary to attract the attention of decision-makers. According to the calculated results, the primary separator and fuel gas scrubber have the highest risk of gas leakage, while crude oil separator has the highest risk of oil leakage.

Table 11. Ranking comparison of taking different α value (Improved fuzzy TOPSIS using the subjective-variable integrated weight method).

	$\alpha = 0$		$\alpha = 1$		$\alpha = 2$		$\alpha = 3$		$\alpha = 4$	
Failure Modes	C_n	**Ranking**	C_n	**Ranking**	C_n	**Ranking**	C_n	**Ranking**	C_n	**Ranking**
FM_1	0.037	4	0.043	2	0.052	2	0.063	1	0.076	1
FM_2	0.034	8	0.033	9	0.033	9	0.032	9	0.032	10
FM_3	0.034	7	0.036	6	0.036	7	0.036	7	0.037	7
FM_4	0.034	6	0.035	7	0.036	6	0.037	6	0.037	6
FM_5	0.033	9	0.034	8	0.035	8	0.036	8	0.037	8
FM_6	0.035	5	0.037	5	0.040	5	0.042	4	0.045	3
FM_7	0.027	12	0.026	12	0.024	12	0.023	12	0.022	12
FM_8	0.030	11	0.029	11	0.028	11	0.027	11	0.026	11
FM_9	0.047	1	0.051	1	0.056	1	0.060	2	0.065	2
FM_{10}	0.039	3	0.040	4	0.041	4	0.042	3	0.044	4
FM_{11}	0.040	2	0.041	3	0.042	3	0.042	5	0.042	5
FM_{12}	0.031	10	0.031	10	0.031	10	0.032	10	0.033	9

In summary, by comparing the calculated results of improved fuzzy TOPSIS and fuzzy TOPSIS, it is verified that the former is reasonable and effective in introducing fuzzy evidence reasoning and the comprehensive weighting method, and solves the problems caused by the uncertainty, diversity, and subjective weight of O, S, and D ratings. Therefore, the proposed approach can reduce the risk priority ranking error of failure mode and provide a more scientific basis for risk decision-making.

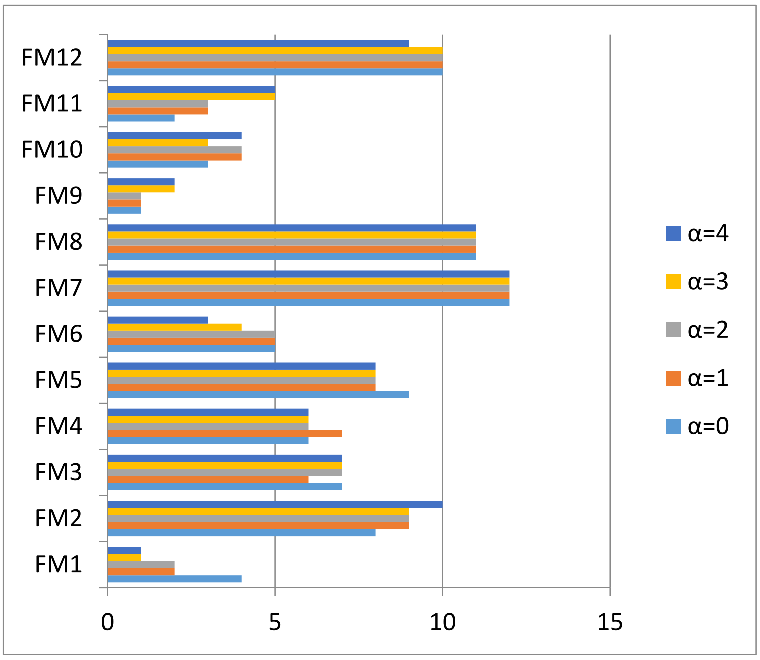

Figure 6. Ranking comparison of taking different α value (improved fuzzy TOPSIS using subjective-variable integrated weight method).

The risk identification approach based on a fuzzy TOPSIS integrated fuzzy evidential reasoning approach is proposed in this paper. In specific applications, the implementation process of the method will be limited due to the limitation of the number of experts, but in specific embodiments, the implementations will be constantly updated with the increase in the number of experts and the wider adoption of opinions in the later stage, so as to get more convincing results. Somehow, the opinions of the experts in this paper represent the real risk identification results to some extent.

In the process of the proposed method, some other secondary factors are not also considered, and these factors may also have a certain deviation and influence on the results. For example, in view of the fuzziness of the description language in the analysis, using the simplification of fuzzy numbers to describe the language will have an impact on the evaluation and results. The analysis data mainly comes from expert experience and historical statistics, which will inevitably bring certain subjective errors. How to minimize the subjective errors caused by individuals is a problem that needs to be further discussed in the future.

6. Conclusions

FMEA (failure mode and effect analysis) is an important safety and reliability analysis tool that is widely used in a wide range of industries. Due to its difficulty in acquiring precise assessment information on failure modes, the defects in the traditional RPN (risk priority number) modes, and the difficulty in building a complete fuzzy rule base, we proposed a new FMEA using the FER (fuzzy evidence reasoning) approach and fuzzy TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution), which adopt the comprehensive weighting method.

The potential application of the proposed approach is examined and illustrated in FPSO (floating production storage and offloading system) oil and gas processing systems. It is more in line with the engineering practice to assign different weights to O (occurrence), S (severity), and D (detectability) for considering the influence of O, S, and D on the risk when determining the risk of the failure mode. When determining the objective weight of O, S, and D of failure mode, the variable weight method and entropy weight method start from the horizontal and vertical directions of O, S, and D of failure mode, respectively. That is, the weight of variable weight is adjusted according to the rating of O, S, and D in the same failure mode. Entropy weight is to adjust the weight of O (S or D) of any failure mode according to the values of O (S or D) in all failure modes. It provides a new idea for determining the weight. Further, the variable weight method is the comprehensive effect of assigning more weight to the larger value in O, S, and D, and less weight to the smaller value; and then by increasing the variable weight coefficient α, the risk result of failure mode can be magnified to attract attention. In particular, the proposed approach uses a fuzzy confidence structure to represent the uncertainty, diversity, and absence of O, S, and D ratings and give different beliefs.

The improved FMEA method in this paper can be used in situations where the data obtained is incomplete and inaccurate, and in those systems where it is difficult to obtain reliable data. In determining the risk of failure mode, different evaluation indicators (risk factors) are considered to have different importance; different risk factors are given different weights; and more risk factors can be added as needed, making the improved FMEA more practical and flexible.

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