Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 9743396, 16 pages
https://doi.org/10.1155/2022/9743396

Research Article

Risk Assessment Method for Ship Based on Improved Fuzzy Multicriteria Decision-Making

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Received 4 September 2022; Revised 20 November 2022; Accepted 1 December 2022; Published 13 December 2022

Academic Editor: Chiranjibe Jana

Aimed at the uncertainties and relevance issues during the risk factor identification in multicriteria decision-making, this paper presents a ship risk assessment model based on the improved fuzzy multicriteria decision-making. First, on the basis of safety assessment and importance judgment of risk sources conducted by experts, the peer-to-peer consensus model is employed to integrate the relative importance of risk sources and obtain the weight of experts; the weight of risk factors is then determined by nonlinear programming model according to the experts' preference for risk sources; finally, the risk assessment is carried out using the MULTIMOORA method and the final ranking of the alternatives is determined by means of the fuzzy number quantitative calculation method. Analysis and research are conducted on specific causes of ship engine room fires, and the results are compared with outcomes of the traditional MULTIMOORA method and the fuzzy analytic hierarchy process based on Monte Carlo simulation. It is concluded that the calculated ranking results are more reasonable, hence verifying the superiority of this model.

1. Introduction

The shipping industry, with vessels as the mainstay of water transportation, is a typical heavy asset industry [1]. The occurrence has the characteristics of great harm, bad influence, and a relatively small number [2, 3]. Over the years, ship safety has always been an important research topic and content in the international shipping field and has always been the work of shipping units and maritime management departments at home and abroad. Its risk assessment is a complex system engineering, which is not only affected by the static and dynamic information of the ship itself, but also involves the operation task, personnel allocation, policies and regulations, and the uncertain information of navigation waters to a certain extent [4, 5]. At the same time, the assessment process is also contingent on the subjectivity of experts and limited statistics, increasing the fuzziness and uncertainty of ship risk assessment [6]. Adopting modern scientific methods to analyze the risk posed by major safety accidents including ship fire, collision, and capsizing, and taking effective countermeasures according to the assessment results are of great significance to ensuring the safety and economic benefits of the shipping industry [7].

In recent years, the risk assessment of ship engine room fire has attracted the attention of a growing number of scholars. The advent of a plethora of assessment methods and the rapid development of monitoring technology makes it possible to conduct ship risk assessment and analysis on the basis of measured data or expert evaluation. Aided by the fuzzy set theory, Senol et al. [8] conducted a causal investigation on water tank fouling and used the experts' opinions as a mandatory data source to establish the "Dirty Tank Model" based on the Bayesian network. According to this model, the risk prevention strategy during oil tank cleaning was formulated to improve cleaning efficiency. Arici et al. [9] employed the fuzzy bow-tie method to quantitatively analyze the risks of ship cargo operations, further enriching the formal safety assessment (FSA) method. Qiao et al. [10] introduced an analysis framework that combines human factor analysis and classification system with business process management, i.e., the multidimensional analysis model of accident causes (MAMAC), in which the intuitionistic fuzzy set theory and the Bayesian network are integrated to analyze the dynamic human factors of the system. Pan's et al. [11] work combined the interval-valued fuzzy sets, the improved Dempster–Shafer (D-S) evidence theory, and the fuzzy Bayesian network and then proposed a new risk analysis method to provide systematic decision support for the whole-life-cycle safety assurance of complex systems under uncertain conditions.

The multiple multiobjective optimization by ratio analysis (MULTIMOORA) [12] was developed by Brauers and Edmundas based on multiobjective optimization on the basis of ratio analysis (MOORA) [13] in 2013. Compared with other safety assessment methods, the adopted assessment methods and steps are more standardized and reasonable and hence widely employed in risk assessment. Combining the fuzzy set theory [14] with the ordered weighted average (OWA) operator [15], it takes into account the opinions and suggestions of a variety of experts and makes a comprehensive judgment on different risk factors using relevant methods. Therefore, the obtained evaluation results tend to be more accurate and reliable, and their strong adaptability enables them to be cited over a considerable period of time. Wenting [16] proposed a matrix game approach to express the tendency and attitude of decision-makers towards risks and used the prospect theory to establish a decision matrix aimed at enhancing the capacity of collecting and processing information, thus forming a new method of aggregating hesitant fuzzy language information. Wenting [17] employed the information entropy method to determine the criterion weight without resorting to prior knowledge, established the compliance matrix based on the entropy model of risk assessment, and formed a method for determining the index weight of safety risk assessment (SRE) based on the information entropy with the help of the average recognition degree and the cognitive combination degree. Hybrid [18] constructed the decision matrix of trapezoidal fuzzy numbers. To some extent, these methods have overcome the shortcomings of traditional ship risk assessment methods; that is, the assessment value is overly "accurate," thereby strengthening the ability to describe the risk situation. At the same time, some experts have adopted TOPSIS, DEMATEL, AHP, GRA, VIKOR, and other methods to further enhance the ranking ability of multicriteria decision-making. For example, Liang and Xu [19] constructed a multistage decision support framework based on MCDM and TOPSIS to calculate a reasonable alternative ranking; Chen et al. [20] combined the Choquet integral and the MULTIMOORA method to obtain the prioritization of corrective actions. These methods greatly strengthened the evaluation ability of multicriteria decision-making and provide methods and a theoretical basis for ship risk assessment.

However, the current research mainly targets the risk factors related to ship status and environment, such as the impact of speed, sea conditions, and human factors on ship navigation [21–23]. With regard to the fire scenarios of the ship engine room, the existing models tend to ignore the fact that as the experts are unfamiliar with each other, it is thus difficult for them to assess the subjective weights. In terms of their uncertain preferences of different risk sources in a variety of operating environments, there is still a lack of systematic research on risk factor identification based on weight determination, risk factor preference, and risk source ranking.

In view of this, the paper endeavors to propose a new method to solve the problems arising from multicriteria decision-making based on the intuitionistic fuzzy number, peer-to-peer consensus model, nonlinear programming model, and MULTIMOORA. First, intuitionistic fuzzy number is introduced to resolve the limitation of the experts' cognitive uncertainty expression under limited information, and a triangular intuitionistic fuzzy number (IFN) evaluation table of risk sources is established [24]; second, the transfer of expert opinions is weighted by the Markov chain on finite state spaces, and then a consensus model is formed by group analytic hierarchy process (AHP) to obtain the expert weight [25]; the nonlinear programming model [26] is introduced to determine the weight of risk factors using the experts' preference; the triangular intuitionistic fuzzy number is applied to the fire risk assessment, and combined with the MULTIMOORA method, a ship risk assessment method based on improved fuzzy multicriteria decision-making is proposed to identify key risk factors; finally, the fuzzy number quantitative calculation method [27] with intuitionistic attributes is adopted to identify the final ranking of alternatives and improve the effectiveness of the model. The proposed model is then verified by using the engine room fire risk assessment of a ship as an example. This method integrates intuitionistic fuzzy sets, peer consensus model, nonlinear programming model, MULTIMOORA method, and fuzzy number quantitative calculation into the identification of risk factors and the risk analysis of dangerous events. Taking safety importance, time, and reliability as risk factors as constraint information, the risk of dangerous events in these evidence cases is analyzed by constructing a risk analysis model. This study is applicable to all stages of event occurrence, development, and even evolution, so it is more universal in assisting decision-making. Table 1 shows a brief review of major related literature.

The paper is arranged as follows. The intuitionistic fuzzy number, the MULTIMOORA method, and other related knowledge are introduced in the first section. The second section focuses on the model of the extended MULTIMOORA method. In the third section, a case study is provided to verify the effectiveness and practicability of the proposed method. Finally, the conclusion is summed up in Section 4.

2. Basic Theory

2.1. Intuitionistic Fuzzy Sets (IFSs) and Related Theories. In the study of multicriteria decision-making methods, in order to overcome the shortcomings of fuzzy sets that only use membership functions to describe the degree of uncertainty and it is difficult to reflect the degree of hesitation of decision-makers, Atanassov proposed an IFS with more comprehensive information expression. In IFS, membership

Table 1: A brief review of major related literature.

Studies	Risk assessment model	Fuzzy set theory	Expert opinion	Expert weight	Historical data	Risk factor
Senol et al.	Dirty tank model	Yes	Yes	Yes	No	No
Arici et al.	Fuzzy bow-tie method	Yes	Yes	Yes	No	Yes
Qiao et al.	MAMAC	Yes	Yes	Yes	Yes	No
Pan et al.	Improved fuzzy Bayesian network	Yes	Yes	Yes	Yes	No
Wang et al.	Matrix game approach	Yes	Yes	Yes	No	No
Jang et al.	SRE	No	Yes	Yes	No	Yes
Hybrid et al.	Decision matrix	Yes	Yes	No	No	Yes
Liang et al.	Multistage decision	Yes	Yes	Yes	No	No
Chen et al.	Improved MULTIMOORA method	Yes	Yes	Yes	No	No

function, nonmembership function, and hesitation degree are introduced to describe the three attitudes of decision-makers in decision-making problems: affirmation, negation, and hesitation. So far, the theory of intuitionistic fuzzy sets has been further developed: different algorithms and comparison methods are defined; a series of fuzzy information measures such as distance measure, similarity measure, correlation coefficient, and fuzzy entropy are proposed. In addition, the methods of information fusion in an intuitionistic fuzzy environment mainly include the ranking method based on TOPSIS (TOPSIS and VIKOR), the ranking method based on priority relation (ELECTRE and PROMETHE), the ranking method based on prospect theory (TODIM), and a series of aggregation operators. It is widely used to solve decision problems in various fields.

Definition 1 (See [28]). Let B be an intuitionistic fuzzy set on the domain E, then B is defined as the following form:

$$B = \{\langle x, \mu_B(x), \nu_B(x)\rangle | x \in E\}, \tag{1}$$

is the membership function of element.Where $\mu_B(x)$ is the subordinate function of element $x \in E$, $\nu_B(x)$ is the non-subordinate function of element $x \in E$, where $\mu_B(x) \subset [0,1]$, $\nu_B(x) \subset [0,1]$, and satisfies $0 \le \mu_B(x) + \nu_B(x) \le 1$. For any $x \in E$, there is $\pi_B(x) = 1 - \mu_B(x) - \nu_B(x)$, and in $\pi_B(x)$, element x is defined as the hesitation degree of the intuitionistic fuzzy set.

Definition 2 (See [29]). The following relationship exists between IFS and the qualitative term IFN, as shown in Table 2.

The risk degree of the system is subjectively expressed by experts based on the expression category of qualitative terms. Combined with the IFN evaluation table, aggregation is achieved in the formula [30]:

$$\begin{aligned}\alpha_{ij} &= Agg\left(\alpha_{ij}^1, \alpha_{ij}^2, \cdots, \alpha_{ij}^n\right) \\ &= \sum_{k=1}^{n} \lambda_k \alpha_{ij}^k,\end{aligned} \tag{2}$$

where $\alpha_{ij} = (u_{ij}, \nu_{ij}, w_{ij})$ is the membership function part of the final aggregation of IFN, $\alpha_{ij} = (u_{ij}^k, \nu_{ij}^k, w_k^k)$ is obtained by transforming IFN into corresponding qualitative terms according to the experts' opinions, λ is the weight of each expert, λ_s is the weight of each expert for the i-th scheme, $\lambda_k > 0\,(k = 1, 2, \cdots, n)$ and $\sum_{n=1}^{k} \lambda_k = 1$ are satisfied.

Definition 3. Defuzzification is a technique that converts fuzzy numbers into definite real numbers. In this paper, the center of gravity calculation method of triangular fuzzy numbers [31] is used to defuzzify IFN. The specific steps are as follows:

Let IFN be $\tilde{X} = (\mu_B(x); \nu_B(x)) = (\tilde{x}_1^l, \tilde{x}_1^m, \tilde{x}_1^u; \tilde{x}_2^l, \tilde{x}_2^m, \tilde{x}_2^u)$, and take the membership function $\mu_B(x)$ as an example.

(1) Calculate the center of gravity, and the center of gravity of the membership function $\mu_B(x) = (\tilde{x}_1^l, \tilde{x}_1^m, \tilde{x}_1^u)$ is $G_{\tilde{X}} = (\tilde{x}_1^l + \tilde{x}_1^m + \tilde{x}_1^u/3)$

(2) Determine the confidence interval. According to the position of the center of gravity in the triangle, identify the ratio of the cut set to the fuzzy set $\lambda = 1/3$ through Murakami's approach, then the confidence interval of $\tilde{X}$ is $\tilde{X}_+ = [1/3\tilde{x}_1^m + 2/3\tilde{x}_1^l, 1/3\tilde{x}_1^m + 2/3\tilde{x}_1^u]$.

(3) Weight calculation. Use the ratio of the median value to the confidence interval of the fuzzy number to calculate the weight standard, namely

$$\frac{\tilde{x}_1^m}{\left[\left(1/3\tilde{x}_1^m + 2/3\tilde{x}_1^u\right) - \left(1/3\tilde{x}_1^m + 2/3\tilde{x}_1^l\right)\right]} = \frac{\tilde{x}_1^m}{\left[2/3\left(\tilde{x}_1^u + \tilde{x}_1^l\right)\right]}. \tag{3}$$

(4) Weighted multiplication. The center of gravity multiplied by the standard weight is the corrected accurate value X.

$$X = G_{\tilde{X}}\left(\frac{\tilde{x}_1^m}{\left[2/3\left(\tilde{x}_1^u + \tilde{x}_1^l\right)\right]}\right). \tag{4}$$

2.2. MULTIMOORA Method. In 2010, Brauers and Zavadskas [32] added complete multiplication to the two sub-methods of the original MOORA, forming the MULTIMOORA method. In MULTIMOORA, m alternative schemes $S = \{s_1, s_2, \cdots, s_m\}$ and n criterion indexes $C = \{c_1, c_2, \cdots, c_n\}$ are organized into a decision matrix $X = (x_{ij})_{m\times n}$, where x_{ij} is the decision value of scheme s_i under criterion c_j, and the decision matrix can be standardized [33].

Definition 4. Proportional system method

First, the decision matrix can be normalized by using the following formula:

Table 2: Corresponding relationship table between the qualitative term and IFN value.

Qualitative terms	Corresponding IFN value
Very low (VL)	(0.00, 0.04, 0.08; 0.00, 0.04, 0.08)
Low (L)	(0.07, 0.13, 0.19; 0.06, 0.13, 0.20)
Fairly low (FL)	(0.17, 0.27, 0.37; 0.15, 0.27, 0.39)
Medium (M)	(0.35, 0.50, 0.65; 0.32, 0.50, 0.68)
Fairly high (FH)	(0.62, 0.73, 0.82; 0.61, 0.73, 0.85)
High (H)	(0.81, 0.87, 0.93; 0.79, 0.87, 0.95)
Very high (VH)	(0.92, 0.96, 1.00; 0.92, 0.96, 1.00)

$$\widetilde{x}_{ij}^{*} = \left(\widetilde{x}_{ij}^{l*}, \widetilde{x}_{ij}^{m*}, \widetilde{x}_{ij}^{u*}\right) = \left(\frac{x_{ij}^{l}}{x_{ij}^{u*}}, \frac{x_{ij}^{m}}{x_{ij}^{u*}}, \frac{x_{ij}^{u}}{x_{ij}^{u*}}\right), \tag{5}$$

$$x_{ij}^{u*} = \sqrt{\sum_{i=1}^{m} \left(x_{ij}^{u}\right)^{2}}. \tag{6}$$

The evaluation value of the alternatives can be obtained by the following formula:

$$y_i^* = \sum_{j=1}^{g} x_{ij}^* - \sum_{j=g}^{n} x_{ij}^*, \tag{7}$$

where $j = 1 - g$ indicators are benefit indicators, $j = g - n$ indicators are cost indicators, and y_i^* represents the evaluation value of each scheme. Therefore, the larger the evaluation value, the better the condition of the scheme at present. The scheme is hence ranked as follows:

$$S_{rs}^* = \left(s_i \mid \max_i y_i^*\right). \tag{8}$$

Definition 5. Reference point method.

According to the standard decision matrix $X^* = (x_{ij}^*)_{m\times n}$, the reference point of each criterion can be obtained as follows:

$$r_j^* = \begin{cases} \max_i x_{ij}^*, & \text{if } j \le g, \\ \min_i x_{ij}^*, & \text{if } j > g. \end{cases} \tag{9}$$

From this, it can be obtained that the deviation between the evaluation value of each scheme and the reference point is $|x_{ij}^* - r_j^*|$, and the optimal scheme is as follows:

$$S_{rp}^* = \left(s_i \middle| \min_i \left(\max_j \left|x_{ij}^* - r_j^*\right|\right)\right). \tag{10}$$

Definition 6. Complete multiplication.

In the standard decision matrix, the evaluation value of each scheme under complete multiplication yields as follows:

$$\begin{aligned} U_i^* &= \frac{A_i}{B_i} \\ &= \frac{\prod_{j=1}^{g} x_{ij}^*}{\prod_{j=g}^{n} x_{ij}^*}, \end{aligned} \tag{11}$$

where A_i represents the normalized product of the benefit indicators, and B_i represents the normalized product of the cost indicators. The larger the ratio, the better the scheme is under current conditions. Therefore, the optimal scheme is as follows:

$$S_{fm}^* = \left(s_i \middle| \max_i U_i^*\right). \tag{12}$$

3. Ship Risk Assessment Method Based on Improved Fuzzy Multicriteria Decision-Making

The traditional fuzzy multicriteria decision-making approach determines the risk priority of each failure mode by considering the score of risk sources, and values of different risk factors are identified by clear-cut values. In order to resolve the uncertainty and problems of expert expression in the process of risk assessment, this paper uses intuitionistic fuzzy numbers instead of exact values to figure out the fuzzy rating of risk sources. As the evaluation value of each risk source is supplied by multiple experts who are unfamiliar with each other, it is thus difficult for them to provide subjective weight values. The evaluation process takes the uncertainty preferences of experts to risk sources into consideration. Therefore, this paper puts forward an improved fuzzy multicriteria risk assessment method. This hybrid method mainly comprises four stages, namely, identifying risk sources, determining expert weights, calculating risk factor weights, and achieving the prioritization of risk sources. First, the risk assessment information is expressed by triangular fuzzy numbers, and the weights of experts are determined by using the peer-to-peer consensus model. The change in the risk assessment matrix before and after normalization is then analyzed by means of the nonlinear programming model and experts' preferences for each risk source, and the weight of each risk factor is obtained. Finally, the MULTIMOORA method is employed to determine the priority of all risk sources, and the fuzzy number quantitative calculation method is adopted to derive the final ranking.

The proposed model provides a more reasonable risk analysis framework for fuzzy multicriteria decision-making. The proposed improved fuzzy multicriteria model is outlined in Figure 1.

3.1. Hazard Analysis and Evaluation of Qualitative Terms.

Hazard analysis forms a crucial part of the system risk assessment process. It is mainly used to identify risk sources, causes, and impacts and systematically analyze the

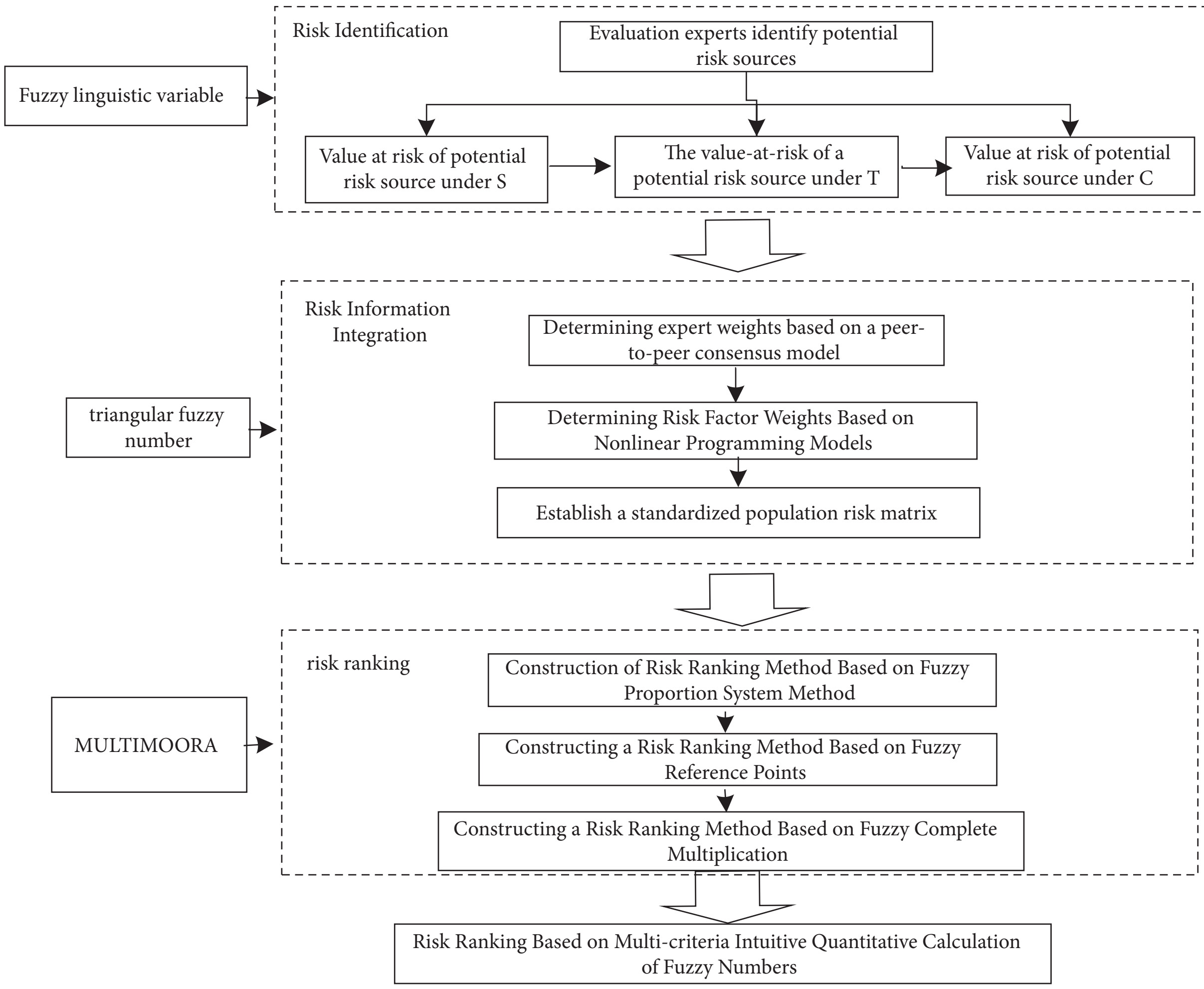

Figure 1: Risk ranking process based on improved MULTIMOORA method.

relationship between subsystems, components, personnel, and operating environments. In this paper, the system is analyzed, and the faults endangering the system are established. Each risk source point $A = \{a_1, a_2, \cdots, a_m\}$ is obtained, and the failure probability ranking table of each fault node is determined in accordance with the previously collected data and literature.

Experts are responsible for conducting qualitative term evaluation on all risk sources of the system from all aspects of risk factor $C = \{c_1, c_2, \cdots, c_n\}$, and the language evaluation table X for risk sources is compiled. The importance of each risk source is compared in pairs to form the importance judgment matrix H. Next, the corresponding relationship between triangular IFN and fuzzy qualitative terms is used to process the language evaluation table and form the triangular IFN evaluation table of risk sources of each expert.

3.2. Determination of Expert Weight. According to the peer-to-peer consensus model, the following formula is used to calculate the consensus degree of any two experts.

$$\begin{aligned} ICI_{pq} &= \frac{1}{n^2} e^T H_p \bullet H_q^T e \\ &= \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij(p)} a_{ji(q)}, \end{aligned} \tag{13}$$

where ICI_{pq} represents the degree of agreement between experts p and q, the smaller the value, the higher the agreement; n represents the number of judgment indicators; e is the identity matrix; H is the judgment matrix of experts; a is the judgment scale.

If the disagreement between experts p and q is the highest, H_p and H_q shall be corrected. The formula is as follows:

$$a_{ij(p)}^{k+1} = \left(a_{ij(p)}^{k}\right)^{\alpha_p^k} \left(a_{ij(q)}^{k}\right)^{1-\alpha_p^k}, \tag{14}$$

$$a_{ij(q)}^{k+1} = \left(a_{ij(q)}^{k}\right)^{\alpha_q^k} \left(a_{ij(p)}^{k}\right)^{1-\alpha_q^k}, \tag{15}$$

where k is the number of iterations; α_p^k and α_q^k are parameters, as follows:

$$\alpha_p^k = 1 - \frac{\sum_{i=1,i\neq p,q}^{m} ICI_{pi}}{2\left(\sum_{i=1,i\neq p,q}^{m} ICI_{pi} + \sum_{i=1,i\neq p,q}^{m} ICI_{qi}\right)}, \tag{16}$$

$$\alpha_q^k = 1 - \frac{\sum_{i=1,i\neq p,q}^{m} ICI_{pi}}{2\left(\sum_{i=1,i\neq p,q}^{m} ICI_{pi} + \sum_{i=1,i\neq p,q}^{m} ICI_{qi}\right)}. \tag{17}$$

When $I_{pq} \leq \varepsilon$, it is considered that experts have reached a consensus, and $\varepsilon = 1.01$ is usually taken as the control value of expert consensus.

Then, the weight of each expert is as follows:

$$\lambda_i = \frac{\sum_{j=1}^{n}\left(\varepsilon - ICI_{ij}\right)}{\sum_{i=1,j=1}^{n}\left(\varepsilon - ICI_{ij}\right)}. \tag{18}$$

3.3. Weight Calculation of Risk Factors Based on the Nonlinear Programming Model. According to the importance weight $\lambda = \{\lambda_1, \lambda_2, \cdots, \lambda_p\}$ of the experts, data gathered from the hired experts are compiled into the comprehensive risk assessment table of risk sources by formula (1), and then the assessment table is calculated by using the standardized formula (3) to obtain the standardized triangular IFN risk assessment matrix $X = (x_{ij}^*)_{m\times n}$.

According to the risk assessment matrix provided by experts and the normalized risk assessment matrix, the following optimization model is constructed as follows:

$$\begin{aligned} \min F(W) &= \sigma D(W) + (1-\sigma)E(W) \\ &= \sum_{j=1}^{n}\left\{\left[\sigma\frac{1}{\sum_{i=1}^{m} s\left(x_{ij}^*, V_i\right)} + (1-\sigma)\sum_{k=1}^{m}\sum_{i=1,i<k}^{m} s\left(x_{ij}, x_{kj}\right)\right]\omega_j\right\} \\ \text{s.t.} &\sum_{j=1}^{n}\omega_j^2 = 1, \omega_j > 0, j \in N, \end{aligned} \tag{19}$$

where $D(W)$ is the attribute weight, W is the total deviation of the subjective and objective preference information (attribute value) of the experts, $E(W)$ is the total deviation of each alternative, $0 \leq \sigma \leq 1$, and it represents the preference of the experts for the subjective and objective weight determination method, usually $\sigma = 0.5$.

$s(x_{ij}^*, V_i)$ is the similarity between the objective preference value of the experts for x_i^* under risk factor c_j and the preference information V_i of experts for scheme x_i^*, $s(x_{ij}, x_{kj})$ indicates the similarity between the alternatives under risk factor c_j, which can be obtained by the method of Lagrange multipliers:

$$\sum_{j=1}^{n}\left\{\left[\sigma\frac{1}{\sum_{i=1}^{m} s\left(x_{ij}^*, V_i\right)} + (1-\sigma)\sum_{k=1}^{m}\sum_{i=1,i<k}^{m} s\left(x_{ij}, x_{kj}\right)\right]\omega_j\right\} + \mu\left(\sum_{j=1}^{n}\omega_j^2 - 1\right). \tag{20}$$

Find the partial derivatives of ω_j and μ, and make them equal to 0, then

$$\begin{aligned} \frac{\partial L\left(\omega_j, \mu\right)}{\partial \mu} &= \sum_{j=1}^{n}\omega_j^2 - 1 \\ &= 0. \end{aligned} \tag{21}$$

Then, the weight can be obtained as follows:

$$\omega_j = \frac{\sigma\left(1/\sum_{i=1}^{m} s\left(x_{ij}^*, V_i\right)\right) + (1-\sigma)\sum_{k=1}^{m}\sum_{i=1,i<k}^{m} s\left(x_{ij}, x_{kj}\right)}{\sum_{j=1}^{n}\sum_{j=1}^{n}\left\{\left[\sigma\left(1/\sum_{i=1}^{m} s\left(x_{ij}^*, V_i\right)\right) + (1-\sigma)\sum_{k=1}^{m}\sum_{i=1,i<k}^{m} s\left(x_{ij}, x_{kj}\right)\right]\omega_j\right\}}. \tag{22}$$

The similarity of the two normal triangular fuzzy numbers is calculated as follows (using the membership function as an example):

The max similarity of the triangular fuzzy numbers as follows:

$$S_{\max}(\tilde{a},\tilde{b}) = \frac{a^l b^l + a^m b^m + a^u b^u}{\max\left[\left(a^l\right)^2 + \left(a^m\right)^2 + \left(a^u\right)^2, \left(b^l\right)^2 + \left(b^m\right)^2 + \left(b^u\right)^2\right]}. \quad (23)$$

The min similarity of the triangular fuzzy numbers as follows:

$$S_{\min}(\tilde{a},\tilde{b}) = \frac{\min\left[\left(a^l\right)^2 + \left(a^m\right)^2 + \left(a^u\right)^2, \left(b^l\right)^2 + \left(b^m\right)^2 + \left(b^u\right)^2\right]}{a^l b^l + a^m b^m + a^u b^u}. \quad (24)$$

According to the definition of similarity, the greater the value of $S_{\max}(\tilde{a},\tilde{b})$ or $S_{\min}(\tilde{a},\tilde{b})$, the greater the similarity between $\tilde{a}$ and $\tilde{b}$.

Therefore, the weight vector of risk factors can be obtained by solving the nonlinear programming model: $\omega = (\omega_1, \omega_2, \cdots, \omega_n)$

3.4. Construction of Comprehensive Risk Assessment Matrix

3.4.1. Fuzzy Ratio System Method. If $\omega^i_{(j)} = \{\omega^i_1, \omega^i_2, \cdots, \omega^i_n\} i = 1, 2, \cdots, m; j = 1, 2, \cdots, n$ is the weight vector of risk factor C under the i th risk source, then the risk ranking formula can be constructed on the basis of the following ratio system:

$$\tilde{R}_i = \sum_{j=1}^{g} \omega^i_{\sigma(j)} \tilde{x}^*_{i\sigma(j)} - \sum_{j=g+1}^{g} \omega^i_{\sigma(j)} \tilde{x}^*_{i\sigma(j)}, \quad (25)$$

where $\tilde{R}_i$ is the risk value of each risk source and can be expressed as (R^l_i, R^m_i, R^u_i).

According to the evaluation contents, ranking results can be obtained by comparing the risk values of risk sources as follows:

$$S^*_{rs} = \left(s_i | \max_i \tilde{R}_i\right). \quad (26)$$

3.4.2. Reference Point Method. The priority of fault nodes can be determined by using this method, and thus the risk parameter reference point r^*_j can be identified as follows:

$$r^*_j = \begin{cases} \max\limits_i x^*_{ij}, & \text{if } j \leq g, \\ \min\limits_i x^*_{ij}, & \text{if } j > g. \end{cases} \quad (27)$$

Next, the following formula is used to calculate the deviation between the risk value and the reference point is as follows:

$$d_{ij} = d\left(\omega^i_{\sigma(j)} r^*_{\sigma(j)}, \omega^i_{\sigma(j)} \tilde{x}^*_{i\sigma(j)}\right), \quad (28)$$

where $d(\omega^i_{\sigma(j)} r^*_{\sigma(j)}, \omega^i_{\sigma(j)} \tilde{x}^*_{i\sigma(j)})$ is the distance function of the triangular fuzzy number, which can be determined by the following formula:

$$d\left(\tilde{A}_1, \tilde{A}_2\right) = \sqrt{\left[\left(a^l_1 - a^l_2\right)^2 + \left(a^m_1 - a^m_2\right)^2 + \left(a^u_1 - a^u_2\right)^2\right]/3}. \quad (29)$$

Finally, the ranking of risk sources can be obtained according to formula (6).

3.4.3. Complete Multiplication. The multiplicative utility values of the cost and benefit risk parameters can be obtained through the following formula:

$$\tilde{A}_i = \prod_{\sigma(j)=1}^{g} \left(\tilde{x}^*_{i\sigma(j)}\right)^{\omega^i_{\sigma(j)}}, \quad (30)$$

$$\tilde{B}_i = \prod_{\sigma(j)=g+1}^{n} \left(\tilde{x}^*_{i\sigma(j)}\right)^{\omega^i_{\sigma(j)}}. \quad (31)$$

The risk value of each risk source can be obtained from formula (8) as follows:

$$\begin{aligned} U^*_i &= \frac{\tilde{A}_i}{\tilde{B}_i} \\ &= \frac{\prod^{g}_{\sigma(j)=1} \left(\tilde{x}^*_{i\sigma(j)}\right)^{\omega^i_{\sigma(j)}}}{\prod^{n}_{\sigma(j)=g+1} \left(\tilde{x}^*_{i\sigma(j)}\right)^{\omega^i_{\sigma(j)}}}. \end{aligned} \quad (32)$$

And the risk value ranking of risk sources can be determined.

3.5. Quantitative Calculation of Fuzzy Numbers Based on the Multicriteria Intuitionistic Approach

(1) Convert the interval number of the reference point method into an intuitionistic fuzzy number [31, 34].

The interval number $d_i = [d^l_i, d^u_i]$ obtained by the reference point method is converted into the intuitionistic fuzzy number $B = [\mu_i(x); \nu_i(x)]$ by the following formula:

$$\begin{cases} \mu_i(x) = \dfrac{d^l_i}{\max_{i=1,2,\cdots,m}\{d^u_i\}}, \\ \nu_i(x) = 1 - \dfrac{d^u_i}{\max_{i=1,2,\cdots,m}\{d^u_i\}}. \end{cases} \quad (33)$$

The result shall meet the requirements of range limitation, boundary characteristics, and monotonicity of mapping.

(2) Calculate the entropy weight σ_j of risk factors

$$\begin{aligned} H_i = &-\frac{1}{n \ln 2}\left[\mu_i \ln \mu_i + \nu_i \ln \nu_i \right. \\ &\left. -(\mu_i + \nu_i)\ln(\mu_i + \nu_i) - (1 - \mu_i - \nu_i)\ln 2\right], \end{aligned} \quad (34)$$

$$\sigma_i = \frac{1 - H_i}{n - \sum_{i=1}^{n} H_i}. \quad (35)$$

(3) Determine the best case A^+ and the worst case A^- of the risk source

$$\begin{cases} A^+ = \{\langle \mu_1, \nu_1 \rangle, \langle \mu_2, \nu_2 \rangle, \cdots, \langle \mu_n, \nu_n \rangle\}, \\ A^- = \{\langle \mu_1, \nu_1 \rangle, \langle \mu_2, \nu_2 \rangle, \cdots, \langle \mu_n, \nu_n \rangle\}. \end{cases} \quad (36)$$

(4) Calculate the relative proximity S_i^+ and S_i^- of each risk source to the optimal solution and the worst solution, and calculate the relative proximity

$$\begin{cases} S_i^+ = \sigma_i \bullet s(\langle A^+ \rangle, \langle \mu_i, \nu_i \rangle), \\ S_i^- = \sigma_i \bullet s(\langle A^- \rangle, \langle \mu_i, \nu_i \rangle), \end{cases} \quad (37)$$

$$P_i = \frac{S_i^-}{(S_i^+ + S_i^-)}, \quad (38)$$

where

$$s(\langle \mu_1, \nu_1 \rangle, \langle \mu_2, \nu_2 \rangle) = 1 - \frac{|2(\mu_1 - \mu_2) - (\nu_1 - \nu_2)|}{3} \times \left(1 - \frac{\pi_1 + \pi_2}{2}\right) \frac{|2(\nu_1 - \nu_2) - (\mu_1 - \mu_2)|}{3} \times \left(\frac{\pi_1 + \pi_2}{2}\right). \quad (39)$$

3.6. Decision Algorithm Based on Improved Fuzzy Multicriteria. The solution algorithm is stated as follows:

(1) Enter $a_i, c_j, H_{ij}, \tilde{\tilde{r}}_{ij}^p, \nu_i, \varepsilon, \sigma$.
(2) Using formula (12) and H_{ij} to find the degree of expert consistency ICI_{pq}.
(3) If $ICI_{pq} > \varepsilon$, proceed to step 4, otherwise to step 5.
(4) Using formulas (14)–(17) to iteratively calculate the degree of expert agreement ICI_{pq}, the iterative calculation converges to $ICI_{pq} \leq \varepsilon$
(5) Using formula (18) to derive expert weight λ_i
(6) The evaluation matrix $\tilde{r}_{ij}^e$ is obtained by using the table of correspondence between qualitative terms and intuitionistic fuzzy sets and $\tilde{\tilde{r}}_{ij}^p$
(7) Using the formulas (5) and (6) and the evaluation matrix $\tilde{r}_{ij}^e$ to obtain the standardized evaluation matrix r_{ij}^*;
(8) Calculating the total deviation between the evaluated value and the preference value by using formulas (23) and (24) and the preference information set ν_i
(9) Using formulas (19)–(22) and parameter σ to obtain the risk factor weight w_j
(10) Using formulas (25) and (26), the ranking result S_{rs}^* of fuzzy ratio system method is obtained;
(11) Using formulas (27)–(29) to obtain the ranking result S_{rp}^* of the reference point method;
(12) Using the formulas (30)–(32), the complete multiplicative ranking result S_{rm}^* is obtained;
(13) Using equations (33)–(35), we obtain the entropy weight σ_i for each risk;
(14) Use equations (36)–(38) to obtain the relative proximity P_i of each risk source;
(15) S_{fm}^* is obtained by formula (39);
(16) End

3.7. An Example of Ship Fire Risk Analysis. Fire is among the three major hazards jeopardizing ship safety. Though characterized by severe impact and huge loss, it is still preventable, and one of the main fire prevention methods is to identify the risk levels of each risk source with accuracy and efficiency and carry out targeted management and maintenance accordingly. In the following section, a comprehensive technical condition assessment model based on multisource data is established according to the operation characteristics of a certain type of ship. While taking into account the safety importance, reliability, and service time, the crew status, operation needs, policies and regulations, convenience, simplicity, and detectability are also considered during the index selection. In the evaluation model, level 1 indicators include high-temperature objects, electrical equipment, and chemical and mechanical thermal energy; 12 elements such as overheating of equipment surface, improper handling of lit cigarette butts, and open fire operation in nonoperation, area are selected as level 2 indicators. The specific indicators in the fire situation assessment model of a certain type of ship are shown in Figure 2. The following part conducts a risk analysis of the ship by means of the new method to verify its feasibility and effectiveness.

Risk assessment of the main risk sources is conducted on an engine room fire accident. The fault analysis of the engine room fire is shown in Figure 2.

Index system of engine room fire factors according to evaluation criteria in Tables 2 and 3, four experts engaged in research of ship safety were invited to evaluate the 12 risk sources in terms of safety importance (S), maintenance time (T), and reliability (C), forming the language evaluation table for each risk source (Table 4). Subsequently, the corresponding relationship between the triangular IFN and fuzzy qualitative terms was used to compile the triangular IFN evaluation table for each expert.

The importance of expert 1, expert 2, expert 3, and expert 4 is judged in Tables 5–8. The experts' opinions on the importance of risk sources, reflected in Tables 5–8, are used to calculate the consensus degree of any two experts in accordance with the peer-to-peer consensus model. Among them, poor consistency was identified between two experts, with a consistency index of $ICI_{PQ} = 1.56$. Iterative correction is carried out until $ICI_{PQ} \leq 1.01$ is satisfied. Finally, the given experts' importance weights are obtained as $\lambda = \{0.236, 0.227, 0.269, 0.268\}$ according to formula (18).

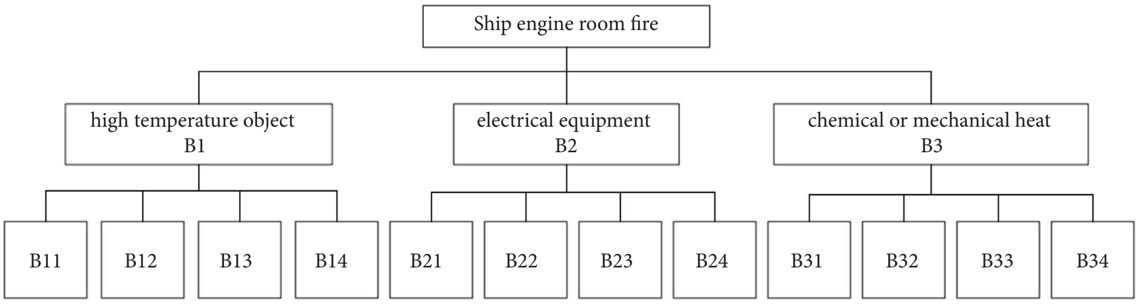

Figure 2: Fault analysis of the ship engine room fire.

Table 3: Index system of engine room fire factors.

Target layer	Factor layer	Indicator layer
Set of fire risk factors in the ship engine room	High-temperature object B_1	Overheating of equipment surface B_{11}
		Improper handling of lit cigarette butts B_{12}
		Open fireworks in nonoperation area B_{13}
		Improper use of fire in the kitchen B_{14}
	Electrical equipment B_2	Equipment short circuit B_{21}
		Sparks produced by improper operation B_{22}
		Illegal electricity use B_{23}
		Failed fire alarm B_{24}
	Chemical or mechanical heat B_3	Equipment seal failure or leakage B_{31}
		Fuel valve left open or pipe rupture B_{32}
		Private storage of flammable and explosive items B_{33}
		Cargo spontaneous combustion B_{34}

Table 4: Language evaluation form of failure points.

	S				*T*				*C*			
	E1	E2	E3	E4	E1	E2	E3	E4	E1	E2	E3	E4
B11	L	VL	M	H	M	VL	M	FL	FL	H	FL	M
B12	M	L	M	H	M	M	VL	H	FL	H	M	M
B13	VH	VH	H	VH	FH	VH	VH	H	H	VH	FH	VH
B14	VL	M	L	L	FL	M	M	L	FL	L	L	FL
B21	M	FH	FL	M	FL	FL	M	FH	L	L	M	L
B22	M	M	FH	FH	M	M	FL	M	FL	M	M	FH
B23	FL	FL	L	FH	M	M	M	M	FL	FL	M	FL
B24	FH	H	H	VH	FL	FL	L	M	H	FH	M	H
B31	M	FL	FL	M	VL	L	L	L	L	FL	L	L
B32	FL	FL	FL	M	VL	VL	VL	L	VL	L	L	VL
B33	M	M	M	FL	FH	M	FL	M	M	M	M	FH
B34	FH	H	H	M	L	L	L	VL	H	H	VH	H

The weights of the four experts indicate that experts 3 and 4 share a fairly consistent understanding of the fault points, while expert 2 understands the importance of the fault points somewhat differently than other experts. This method can effectively eliminate the inaccuracy of judgment resulting from an individual expert's evaluation, and at the same time, it can reflect the expert's personal judgment tendency to a certain extent. It also provides method support for experts navigating subjective weights in unfamiliar situations.

According to formula (2), the expert evaluation table can be combined into the comprehensive risk evaluation table of risk source, and then the table can be sorted into a standardized triangular IFN risk evaluation matrix by using the standardized formula (5).

The fuzzy density table of risk factors is obtained by using the nonlinear programming model of the formula (19). The experts' preference for each risk source is $V = (0.30, 0.35, 0.40, 0.35, 0.45, 0.25, 0.40, 0.50, 0.55, 0.35, 0.30, 0.6)$.

See Table9 for details:

Table 10 shows that in this case, the weight of safety importance is the highest and that of reliability is the lowest, which provides targeted opinions for the risk ranking afterwards.

According to the risk ranking based on the fuzzy ratio system method, the $\widetilde{R}_i$ of each fault point is calculated according to Table 9, and the risk ranking formula (26) is based on the ratio system. The results are shown in Table 11.

Table 5: Expert E1's importance discriminant matrix.

	B11	B12	B13	B14	B21	B22	B23	B24	B31	B32	B33	B34
B11	1	1/3	1/9	1/3	1/3	1/5	1/5	1/7	7	9	1/7	5
B12	1/3	1	1/5	3	3	1/9	1/7	5	5	7	1/5	3
B13	9	5	1	3	1/7	1/5	5	3	7	9	1/3	5
B14	3	1/3	1/3	1	3	1/3	1/7	1/5	5	9	3	7
B21	3	1/3	7	1/3	1	1/5	1/9	3	7	5	1/7	9
B22	5	9	5	3	5	1	1/5	1/3	7	7	1/7	9
B23	5	7	1/5	7	9	5	1	3	9	5	1/3	7
B24	7	1/5	1/3	5	1/3	3	1/3	1	5	7	1/7	9
B31	1/7	1/5	1/7	1/5	1/7	1/7	1/9	1/5	1	3	1/9	1/3
B32	1/9	1/7	1/9	1/9	1/5	1/7	1/5	1/7	1/3	1	1/9	3
B33	7	5	3	1/3	7	7	3	7	9	9	1	5
B34	1/5	1/3	1/5	1/7	1/9	1/9	1/7	1/9	3	1/3	1/5	1

Table 6: Expert E2's importance discriminant matrix.

	B11	B12	B13	B14	B21	B22	B23	B24	B31	B32	B33	B34
B11	1	1/5	1/9	3	5	1/5	1/9	1/3	3	5	1/7	3
B12	5	1	1/7	3	1/3	1/5	1/7	1/3	5	7	9	3
B13	9	7	1	5	3	3	1/3	3	1/5	5	7	9
B14	1/3	1/3	1/5	1	5	3	1/5	3	5	7	1/9	9
B21	1/5	3	1/3	1/5	1	3	1/5	1/3	7	9	1/7	3
B22	5	5	1/3	1/3	1/3	1	1/5	3	5	7	1/5	7
B23	9	7	3	5	5	5	1	5	9	7	1/3	9
B24	3	3	1/3	1/3	3	1/3	1/5	1	7	5	1/3	3
B31	1/3	1/5	5	1/5	1/7	1/5	1/9	1/7	1	3	1/9	1/3
B32	1/5	1/7	1/5	1/7	1/9	1/7	1/7	1/5	1/3	1	1/9	1/5
B33	7	1/9	1/7	9	7	5	3	3	9	9	1	7
12	1/3	1/3	1/9	1/9	1/3	1/7	1/9	1/3	3	5	1/7	1

Table 7: Expert E3's importance discriminant matrix.

	B11	B12	B13	B14	B21	B22	B23	B24	B31	B32	B33	B34
B11	1	1/3	1/9	1/3	1/3	1/5	1/7	1/5	5	7	1/7	1/3
B12	3	1	1/9	3	1/3	1/5	1/7	1/5	7	9	1/7	5
B13	9	9	1	7	5	3	3	5	9	9	3	7
B14	3	1/3	1/7	1	1/3	1/5	1/7	1/3	7	9	1/7	3
B21	3	3	1/5	3	1	1/3	1/7	1/3	7	9	1/5	5
B22	5	5	1/3	5	3	1	1/3	3	7	9	1/3	7
B23	7	7	1/3	7	7	3	1	3	9	9	3	7
B24	5	5	1/5	3	3	1/3	1/3	1	7	9	1/3	5
B31	1/5	1/7	1/9	1/7	1/7	1/7	1/9	1/7	1	3	1/7	1/3
B32	1/7	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/3	1	1/7	1/3
B33	7	7	1/3	7	5	3	1/3	3	7	7	1	7
B34	3	1/5	1/7	1/3	1/5	7	1/7	1/5	3	3	1/7	1

Table 8: Expert E4's importance discriminant matrix.

	B11	B12	B13	B14	B21	B22	B23	B24	B31	B32	B33	B34
B11	1	1/5	1/7	1/3	1/5	1/7	1/5	1/3	7	3	1	1/7
B12	5	1	1/7	5	1/5	1/5	1/7	1/7	7	5	1/5	9
B13	7	7	1	3	9	3	3	5	9	9	3	7
B14	3	1/5	1/3	1	1/3	1/5	1/7	1/3	7	7	1/7	3
B21	5	5	1/9	3	1	1/3	1/7	1/3	5	9	1/5	5
B22	7	5	1/3	5	3	1	1/3	3	7	5	1/5	7
B23	5	7	1/3	7	7	3	1	3	3	9	3	5
B24	3	7	1/5	3	3	1/3	1/3	1	7	3	1/3	3
B31	1/7	1/7	1/9	1/7	1/5	1/7	1/3	1/7	1	3	1/7	1/9
B32	1/3	1/5	1/9	1/7	1/9	1/5	1/9	1/3	1/3	1	1/7	1/7
B33	1	5	1/3	7	5	5	1/3	3	7	7	1	3
B34	7	1/9	1/7	1/3	1/5	7	1/5	1/3	9	7	1/3	1

Table 9: Fuzzy density table of risk factor combination.

Fuzzy measure of risk factors		
$\varphi(S) = 0.38$	$\varphi(T) = 0.32$	$\varphi(C) = 0.30$

Table 10: Standardized risk assessment form for risk sources.

	S	T	C
B11	(0.1450, 0.1803, 0.2155; 0.1340, 0.1750, 0.2160)	(0.1225, 0.1841, 0.2456; 0.1073, 0.1776, 0.2479)	(0.1707, 0.2196, 0.2686; 0.1553, 0.2132, 0.2711)
B12	(0.1813, 0.2280, 0.2746; 0.1662, 0.2213, 0.2764)	(0.209, 0.262, 0.3151; 0.1914, 0.2529, 0.3143)	(0.1934, 0.2487, 0.304; 0.1762, 0.2414, 0.3066)
B13	(0.3940, 0.4141, 0.4342; 0.3802, 0.4020, 0.4238)	(0.4518, 0.4859, 0.5174; 0.4319, 0.4689, 0.5059)	(0.3819, 0.4117, 0.439; 0.3673, 0.3996, 0.4319)
B14	(0.0518, 0.0853, 0.1188; 0.0450, 0.0828, 0.1206)	(0.1281, 0.191, 0.2539; 0.1118, 0.1843, 0.2569)	(0.0565, 0.0942, 0.1318; 0.048, 0.0914, 0.1348)
B21	(0.1606, 0.2170, 0.2714; 0.1461, 0.2106, 0.2752)	(0.1869, 0.2509, 0.3119; 0.1697, 0.2421, 0.3145)	(0.0682, 0.1078, 0.1473; 0.0592, 0.1046, 0.15)
B22	(0.2190, 0.2759, 0.3280; 0.2044, 0.2678, 0.3313)	(0.1662, 0.2415, 0.3167; 0.1459, 0.233, 0.3202)	(0.1784, 0.2382, 0.2955; 0.163, 0.2312, 0.2995)
B23	(0.1167, 0.1574, 0.1957; 0.1070, 0.1528, 0.1985)	(0.1929, 0.2756, 0.3583; 0.1702, 0.2659, 0.3617)	(0.1025, 0.1558, 0.2091; 0.0892, 0.1512, 0.2133)
B24	(0.3516, 0.3810, 0.4083; 0.3361, 0.3699, 0.4037)	(0.1055, 0.162, 0.2186; 0.0911, 0.1564, 0.2216)	(0.3019, 0.3468, 0.3895; 0.2838, 0.3366, 0.3895)
B31	(0.1154, 0.1708, 0.2262; 0.1012, 0.1658, 0.2303)	(0.0295, 0.0599, 0.0904; 0.0244, 0.0578, 0.0913)	(0.0435, 0.076, 0.1084; 0.0367, 0.0737, 0.1108)
B32	(0.0966, 0.1468, 0.1969; 0.0840, 0.1425, 0.2009)	(0.0103, 0.0353, 0.0603; 0.0086, 0.0341, 0.0597)	(0.0163, 0.0397, 0.0632; 0.0136, 0.0386, 0.0636)
B33	(0.1335, 0.1940, 0.2544; 0.1179, 0.1883, 0.2587)	(0.2013, 0.2714, 0.3389; 0.1823, 0.2619, 0.3415)	(0.1983, 0.2637, 0.3266; 0.1812, 0.2559, 0.3306)
B34	(0.2840, 0.3265, 0.3668; 0.2670, 0.3169, 0.3669)	(0.0282, 0.0584, 0.0885; 0.0234, 0.0563, 0.0893)	(0.3942, 0.4198, 0.4455; 0.3759, 0.4075, 0.4391)
r_j^*	(0.3940, 0.4141, 0.4342; 0.3802, 0.4020, 0.4238)	(0.0103, 0.0353, 0.0603; 0.0086, 0.0341, 0.0597)	(0.3942, 0.4198, 0.4455; 0.3759, 0.4075, 0.4391)

Table 11: Risk ranking results based on the fuzzy ratio system method.

Hazard	Relative preference among risk factors	Risk value
B11	(0.0671, 0.0755, 0.0839; 0.0632, 0.0736, 0.0841)	(0.5089, 0.0413)
B12	(0.0600, 0.0774, 0.0947; 0.0548, 0.0756, 0.0964)	(0.2589, 0.0230)
B13	(0.1197, 0.1254, 0.1311; 0.1164, 0.1226, 0.1287)	(2.0691, 0.2673)
B14	(−0.0044, −0.0005, 0.0034; −0.0043, 0.0001, 0.0041)	(0.00004, 0.0000001)
B21	(0.0217, 0.0345, 0.0475; 0.0190, 0.0340, 0.0489)	(0.0693, 0.0030)
B22	(0.0835, 0.0990, 0.1120; 0.0799, 0.0966, 0.1133)	(0.5115, 0.0551)
B23	(0.0134, 0.0184, 0.0224; 0.0130, 0.0183, 0.0237)	(0.0554, 0.0012)
B24	(0.1905, 0.1970, 0.2021; 0.1837, 0.1915, 0.1993)	(5.0065, 1.0033)
B31	(0.0475, 0.0685, 0.0895; 0.0417, 0.0666, 0.0915)	(0.1676, 0.0138)
B32	(0.0383, 0.0564, 0.0745; 0.0333, 0.0548, 0.0763)	(0.1318, 0.0090)
B33	(0.0458, 0.0660, 0.0862; 0.0408, 0.0645, 0.0882)	(0.1617, 0.0129)
B34	(0.2172, 0.2313, 0.2447; 0.2068, 0.2247, 0.2426)	(2.9152, 0.7003)

3.7.1. Risk Ranking Based on the Reference Point Method. First, according to the standardized comprehensive risk assessment matrix in Table 10, the reference point r_j^* of each risk factor is determined through the third step. Then, the risk value of risk factors under the reference point method is calculated by using the formula. The risk ranking of hazard sources based on the reference point method is determined accordingly, and the results are shown in Table 12.

3.7.2. Risk Ranking Based on Complete Multiplication. According to the formula, the whole-process utility values $\widetilde{A}_i$ and $\widetilde{B}_i$ of the cost and benefit risk parameters can be calculated respectively, yielding the risk value U_i^* of the hazard source. The results are shown in Table 13.

The priority ranking results obtained by the ratio system method, the reference point method, and the complete multiplication are integrated by using the multicriteria

Table 12: Risk ranking based on the reference point method.

Hazard	Deviation value between risk factors			Risk value
	S	T	C	
B11	(0.089, 0.299)	(0.049, 0.220)	(0.060, 0.246)	(0.089, 0.299)
B12	(0.071, 0.267)	(0.073, 0.270)	(0.052, 0.228)	(0.073, 0.270)
B13	(0.000, 0.000)	(0.144, 0.379)	(0.003, 0.053)	(0.144, 0.379)
B14	(0.125, 0.354)	(0.051, 0.225)	(0.098, 0.313)	(0.125, 0.354)
B21	(0.076, 0.276)	(0.069, 0.263)	(0.094, 0.306)	(0.094, 0.306)
B22	(0.054, 0.233)	(0.067, 0.259)	(0.055, 0.235)	(0.067, 0.259)
B23	(0.098, 0.313)	(0.078, 0.280)	(0.079, 0.282)	(0.098, 0.313)
B24	(0.013, 0.114)	(0.041, 0.203)	(0.023, 0.150)	(0.041, 0.203)
B31	(0.093, 0.305)	(0.008, 0.089)	(0.103, 0.321)	(0.103, 0.321)
B32	(0.102, 0.319)	(0.000, 0.000)	(0.114, 0.338)	(0.114, 0.338)
B33	(0.085, 0.291)	(0.076, 0.276)	(0.048, 0.219)	(0.085, 0.291)
B34	(0.034, 0.185)	(0.007, 0.087)	(0.000, 0.000)	(0.034, 0.185)

Table 13: Risk ranking based on complete multiplication.

Hazard	Risk value	Preference
B11	(1.808, 1.758, 1.696; 1.837, 1.773, 1.695)	(−41.297, −70.893)
B12	(1.898, 1.735, 1.614; 1.962, 1.750, 1.605)	(−16.027, −26.514)
B13	(1.475, 1.448, 1.424; 1.491, 1.461, 1.433)	(−61.710, −88.369)
B14	(3.779, 3.048, 2.661; 4.006, 3.075, 2.639)	(−12.933, −36.084)
B21	(2.621, 2.240, 2.009; 2.749, 2.260, 1.992)	(−12.572, −26.226)
B22	(1.682, 1.592, 1.524; 1.702, 1.606, 1.518)	(−24.172, −37.386)
B23	(2.646, 2.335, 2.140; 2.739, 2.356, 2.122)	(−16.430, −36.229)
B24	(1.037, 1.107, 1.146; 1.026, 1.117, 1.156)	(16.706, 18.928)
B31	(1.884, 1.723, 1.588; 1.962, 1.739, 1.572)	(−15.119, −24.690)
B32	(1.935, 1.872, 1.729; 2.029, 1.889, 1.706)	(−25.153, −44.69)
B33	(2.091, 1.833, 1.665; 2.182, 1.849, 1.652)	(−12.024, −20.693)
B34	(0.681, 0.800, 0.859; 0.666, 0.807, 0.865)	(5.258, 4.413)

intuitionistic fuzzy number quantitative calculation. The results are shown in Table 14.

It can be seen from Table 14 that the main risks causing fire in the ship engine room are failure of the fire alarm device and open fire operation in nonoperation area. According to the final results, the risk sources can be divided into three levels: high risk (≥ 1.0), medium risk (≥ 0.3), and low risk (< 0.3). Compared with the traditional risk assessment technique, this method cannot only clarify the risk ranking of risk sources but also classify their risk grades. It provides robust data support for ship fire prevention and control.

In order to verify the superiority of the proposed improved fuzzy multicriteria decision-making model, the traditional MULTIMOORA approach is selected for comparative analysis on the basis of the previously mentioned examples. The prioritization results of different methods are shown in Figure 3.

It can be seen from the figure that the risk prioritization results of the improved fuzzy multicriteria decision-making method are significantly different from those of the traditional approach. Results obtained by using the traditional MULTIMOORA method suggest that the risk rankings of equipment surface overheating, improper handling of lit cigarette butts, and improper use of fire in the kitchen are almost the same as that proposed in this paper, which indicates that the weight and status judgment of some risk sources in the ranking process of the new model are consistent with that of the original model, and the two methods share the same ranking mechanism. Failure of fire alarm devices, open fire operation in nonoperation areas, and spontaneous combustion of cargo are considered some of the main causes of ship fire [35], and the hazard ranking obtained by traditional methods fails to fully reflect its importance. Therefore, compared with the traditional MULTIMOORA method, this paper adopts the peer-to-peer consensus model to aggregate the group evaluation information with a highlight on the interaction between risk factors. The improved fuzzy multicriteria decision-making method can be used for comprehensive risk analysis of risk sources.

According to the fuzzy analytic hierarchy process based on Monte Carlo simulation, the risk ranking of 12 risk sources is calculated and compared using the method proposed in this paper. The results are shown in Figure 4:

Monte Carlo-based fuzzy-AHP (MC-FAHP), as a widely used analysis method, can organically combine fuzziness and randomness in uncertain information [36]. The main difference between this model and MC-FAHP is the sequencing of open fire operation in nonoperation areas and equipment seal failure or leakage. According to relevant international research, open fire operations in nonoperation areas and the wind have always been considered paramount risk factors affecting navigation safety worldwide [37] and

Table 14: Final risk ranking.

Hazard	Ratio system method	Reference point method	Complete multiplication	Final result	Final ranking
B11	−0.1591	0.5002	1.0679	0.4086	4
B12	−0.1824	0.5001	0.9621	0.2796	7
B13	0.0805	0.5072	1.5290	1.1023	2
B14	−0.1950	0.5048	0.9623	0.2625	12
B21	−0.1974	0.5008	0.9628	0.2646	10
B22	−0.1588	0.4996	0.9801	0.3217	5
B23	−0.1984	0.5013	0.9625	0.2628	11
B24	1.7907	0.4973	0.8873	2.1807	1
B31	−0.1899	0.5020	0.9615	0.2696	9
B32	−0.1927	0.5034	0.9832	0.2871	6
B33	−0.1904	0.5003	0.9638	0.2731	8
B34	0.2780	0.4966	0.7913	0.5727	3

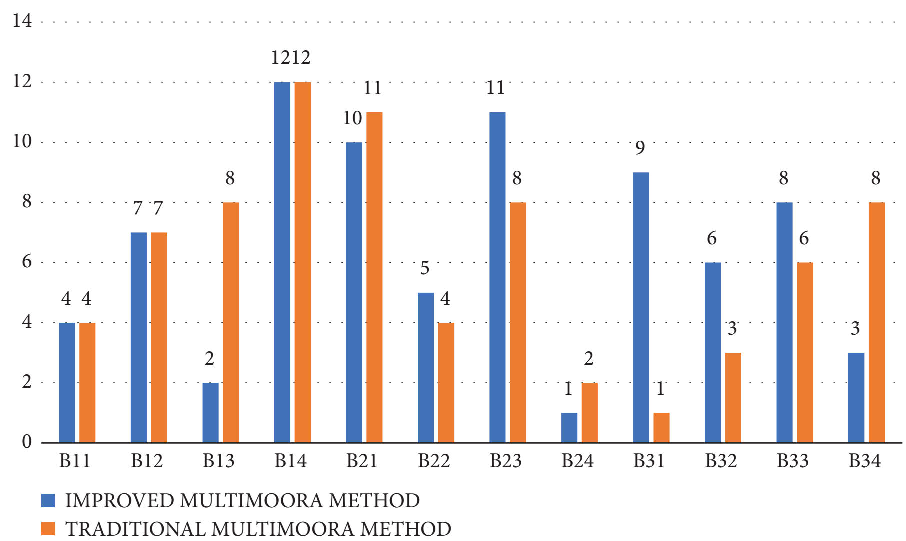

Figure 3: Risk ranking of the improved and traditional MULTIMOORA methods.

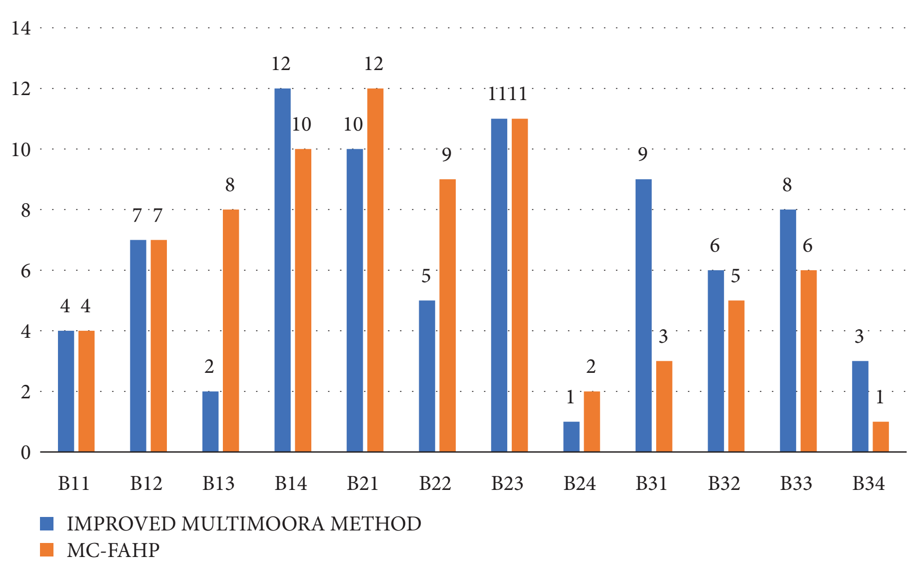

Figure 4: Risk ranking results of improved MULTIMOORA method and MC-FAHP.

also emphatically analyzed in the IMO rules. Therefore, the results calculated based on the improved fuzzy multicriteria decision-making method are consistent with the international research conclusions, which verifies the rationality of the research results.

The comparative analysis shows that the improved fuzzy multicriteria decision-making model can make risk prioritization more accurate and reasonable. If the experts are unfamiliar with each other, the peer-to-peer consensus model can be adopted to reflect the weight of experts more objectively. The application of the nonlinear programming model, which takes the experts' preferences into evaluation, can effectively reduce the deviation caused by the importance of risk sources in different operating environments. More importantly, the improved fuzzy multicriteria decision-making model combines the MULTIMOORA method and the quantitative calculation of fuzzy numbers, inherits MULTIMOORA's many advantages of processing uncertainty evaluation information, makes up for the shortcomings of the traditional approach, and thereby improving the consistency of risk prioritization results with the actual situation.

4. Conclusion

To overcome the shortcomings of the traditional MULTIMOORA method and the fuzzy analytic hierarchy process based on Monte Carlo simulation in risk assessment of ships, this paper proposed an improved MULTIMOORA model that effectively integrates expert opinions and subjective preferences using intuitionistic fuzzy numbers. The model was then employed to rank the risk levels of ship fire risk sources. The feasibility and effectiveness of this method were verified through the fire assessment of a ship. In addition, the results were also compared with those of the traditional MULTIMOORA method and the fuzzy analytic hierarchy process based on Monte Carlo simulation. Comparative analysis showed that the new risk assessment model could effectively resolve the shortcomings of the traditional MULTIMOORA method in the process of ranking the assessment results, such as obtaining the same ranking results and weak persuasiveness. At the same time, it also made up for the significant deviation of some results of the fuzzy analytic hierarchy process based on Monte Carlo simulation from the facts, which made it impossible to divide the hierarchy of risk sources. The rationality and robustness of the proposed method were verified, and some advantages of the proposed method are as follows:

(1) The expert evaluation information was integrated by the peer-to-peer consensus model, which solved the problem of determining the weight of experts given that they were unfamiliar with one another and improved the accuracy of the results;

(2) Considering the degree of preference, the nonlinear programming model was employed to determine the risk factors, which fully considered the importance attached by experts to each risk source during the operation of the ship, making the weight of risk factors closer to the reality;

(3) In the final integration process of the MULTIMOORA method, the multicriteria intuitionistic fuzzy number quantitative calculation method was introduced, which optimized the information aggregation process of the MULTIMOORA method and, to a certain extent, avoiding the loss of a large amount of information during the ranking process. The method yielded more feasible and practical results and improved their robustness.

However, some work still needs to be further improved:

(1) When conducting risk assessment, the acquisition of risk source status is mainly through expert assessment, which is subjective. Therefore, in the subsequent research, it is necessary to further combine the actual situation of the analysis object and use statistical methods to establish a more adaptable reasoning model.

(2) Due to the difficulty of data acquisition, only part of the ship system is analyzed, and the mutual influence and restriction between different systems are not further considered. Therefore, it is necessary to further analyze the interaction between different systems based on specific application scenarios. In future studies, the proposed model can be combined with some more advantageous theories to improve sorting efficiency and accuracy of results.

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 that they have no conflicts of interest.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (Grant no. 51802347).

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