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Article

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A novel integrated method for the risk assessment of ship to ship LNG bunkering operations

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Abstract: In recent years, Liquefied Natural Gas (LNG) has gradually become an alternative fuel for ships. For targeted safety management of ship to ship LNG bunkering, this study aimed to develop a new method to identify, quantify and rank the risk influential factors (RIFs) for fuel spills during the process of ship to ship LNG bunkering. Firstly, starting from the process of ship to ship LNG bunkering, the fuel leakage RIFs of ship to ship LNG bunkering are identified and summarized. Secondly, combining Failure Mode and Effect Analysis (FMEA), Bayesian Networks (BN) based on Fuzzy Belief Rule (FBRBN) and Evidential Reasoning (ER), a risk assessment model is proposed to quantify the risk level of the RIFs. Finally, through the case study of Zhoushan LNG bunkering station, the feasibility and practicability of the established risk evaluation index system and research methods are verified. The results of this study shows that "improper handling by personnel' is the most important RIFs affecting the safety of ship to ship LNG bunkering. Based on the results, targeted preventive measures are also proposed to enhance the safety of ship to ship LNG bunkering.

Key words: Maritime safety; LNG bunkering; Risk assessment; Evidential reasoning; Bayesian Network

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Introduction

Due to the advantages of high calorific value and clean combustion, LNG fuel has gradually become an environmentally friendly alternative fuel for ships (Cao *et al.*, 2023b). With the tightening of the International Maritime Organization's low-sulphur fuel standard and emission zone policy for ships, which has led to an increasing number of LNG-powered ships gradually coming into operation (Gu, 2020). At present, the fuel bunkering methods for LNG-powered ship mainly include five types: tanker, shore station, bunkering ship, barge and floating equipment (Sharma *et al.*, 2022). Among them, ship to ship LNG bunkering has obvious advantages in terms of mobility, quantity and efficiency (Shi *et al.*, 2013). Thus, an increasing number of countries, ports and companies are investing more and more in research and practices in this field year by year (Chen, 2022).

LNG fuel also has the hazardous characteristics of low temperature, flammable, explosive, and prone to evaporation (Tam, 2022). The most serious consequence of an accident during bunkering operations would be the leakage of LNG fuel, which could lead to fires and explosions. As ship to ship LNG bunkering operations mostly take place in harbours and anchorages, an accident will cause incalculable damage to the natural environment and human life (Ha *et al.*, 2022). Therefore, it is necessary to carry out a comprehensive and systematic risk assessment of ship to ship LNG bunkering in order to take corresponding measures in a targeted manner to ensure operational safety.

At its core, risk assessment is an efficient way of designing measures to prevent accidents by measuring the potential influence of an incident on human life, property and other factors through the lens of systems engineering (Wang *et al.*, 2023). Risk assessment of ship to ship LNG bunkering research can help stakeholders understand the RIFs leading to accidents. Furthermore, this study will provide scientific guidance for the development of effective prevention and control measures. However, due to few ship to ship LNG bunkering operations in practice, there is a lack of data to support the risk assessment. At the same time, ship to ship LNG bunkering operation is carried out in port waters, which is inevitably affected by the natural environment and navigational environment. The compatibility of the operating ships and the types of the incoming and outgoing ships are complicated and changeable. Above all, the uncertainty characteristics of the risk assessment of ship to ship LNG bunkering fuel leakage is particularly prominent. Therefore, it is important to choose an appropriate risk assessment method to address these issues in this study.

In the field of risk assessment, FMEA is one of the prevalent approach in process analysis because of its visibility and simplicity (Fan *et al.*, 2022; Fang *et al.*, 2023). In addition, previous research has suggested additional techniques to improve the effectiveness of risk assessment, such as ER, Analytic Hierarchy Process (AHP) and BN. For example, Wang *et al.*, (2023) proposed a risk assessment model to quantify and rank RIFs by combining FMEA, Belief rule based Bayesian Networks (BBN) and ER in the process of Human Evacuation from Passenger Ships. Yu *et al.*, (2020) formulated a semi-qualitative risk model that incorporates BN and ER methods to assess the hazards related to vessel-turbine collisions. Asuquo *et al.*, (2021) utilised a combination of ER and AHP algorithms to evaluate the functional uncertainties of a specific equipment within a marine and offshore facility. Yu *et al.*, (2021) identified and quantified RIFs by combining geometrical analyses of collisions between ship and offshore installation with the BN method, which can be used to assess collision risks involving different navigational environments. Yu *et al.*, (2021b) considers static risk profiles, geographical-dependant risk factors and other local characteristics that affect navigational safety, and combines BN and ER methods to achieve an assessment of the overall risk to coastal vessels.

In the field of ship to ship LNG bunkering risk assessment, Zha (2019) completed a study to assess the operational risk of LNG bunkering ship by combining Formal Safety Assessment and Interval AHP. Gao (2023) used Hierarchical Task Analysis and the IDAC (Information, Decision, and Action in Crew context) model to identify and quantify the RIFs of human factors in LNG bunkering operations. In the field of LNG leakage research, Zhang *et al.*, (2010) analysed the process of accidents such as fire and explosion caused by leakage during LNG storage and transportation. The study developed visualised leakage consequence analysis software based on Gaussian model.

Yu and Dai (2007) carried out a systematic analysis of the causes of storage tank explosion and fires. The study established a fault tree, taking storage tank explosions and fires as top events. Then, by applying a quadratic calculation method to the structural importance coefficients of bottom events, the study located the main RIFs of storage tank safety. Furthermore, Yan (2018) carried out a quantitative analysis of bunkering operation accidents and constructed an LNG fuel leakage model using PHAST software.

In summary, there are well-established methods that can be used to address uncertainty in the risk assessment process. However, in the field of risk assessment for ship to ship LNG bunkering, most of the current studies assess the operational safety of LNG bunkering ships from a macro perspective or extrapolate the consequences of fuel leakage incidents. Meanwhile, since the most serious consequence of an accident during the bunkering operation is the leakage of LNG fuel, which may lead to greater hazards (Chen, 2022), relatively few studies have been conducted to evaluate this critical event as an objective. Therefore, as an emerging technology, the risk assessment of ship to ship LNG bunkering needs to be explored more thoroughly by combining the existing advanced assessment methods.

Therefore, based on related research, this study develops a new risk assessment model to solve the problem of existing uncertainties. This study is able to the quantification and ranking of RIFs leading to the safety of ship to ship LNG bunkering, which improves the safety of ship to ship LNG bunkering operations. The main contributions and innovations of this study as shown below.

(1) From the process of ship to ship LNG bunkering operations, the RIFs of "ship to ship LNG bunkering fuel leakage" are identified on the basis of relevant research, which can be used to identify risks affecting operational safety.

(2) FBRBN and ER algorithms are introduced to address research data limitations and expert knowledge uncertainties. By employing the strengths of FMEA, FBRBN, AHP, ER and utility functions, a model for risk assessment is proposed.

(3) In order to validate the established risk assessment model, the ship to ship LNG bunkering operation near Zhoushan LNG emergency anchorage is used as a case study.

The results of the study show that the established assessment model has good rationality and applicability, and the quantitative indicators affecting the risk events of ship to ship LNG bunkering have been clarified with the help of this case study.

(4) Based on the results of the study, the RIFs for the safety of ship to ship LNG bunkering are analysed and corresponding preventive and control measures are proposed.

RIFs System of Ship to Ship LNG Bunkering Fuel Leakage

In order to improve the current research, it is necessary to establish a reasonable framework for RIFs. Considering the relative complexity of the risk research system of ship to ship LNG bunkering, it is necessary to fully understand the associated attributes and the influence of each RIF when building the framework system. Therefore, this study constructs a RIFs system for ship to ship LNG bunkering fuel leakage from its operational process, with reference to related studies, taking "ship to ship LNG bunkering fuel leakage" as the evaluation objective.

Ship to ship LNG bunkering process

According to the Accident Causation Theory (Lehto and Salvendy, 1991), the subjects involved in ship to ship LNG bunkering operations all have an impact on the safety of the operation. Different RIFs can occur in different parts of the bunkering operation. Therefore, it is feasible to specify the RIFs of different subjects in chronological order from their operation process.

The operational process of ship to ship LNG bunkering consists of three main components, including berthing before the start of the operation, fuel bunkering during the operation and departure after the completion of the operation, as shown in **Table 1**.

TABLE 1. Ship to ship LNG bunkering process.

	I Berthing	II Fuel Delivery	III Departure
Assignment content	LNG bunkering ship and LNG receiving ship berth with each other.	Filling line docking Inspection of detection and alarm systems Pre-cooling and inerting LNG fuel bunkering De-filling lines and monitoring system	LNG bunkering ship and LNG receiving ship depart.

Establishment of RIFs systems

According to General System Theory (Bertalanffy, 1950), a reasonable RIFs framework should follow the principles of systematicity, scientificity, operability and practicality. During the period of ship to ship LNG bunkering operations in **Table1**, RIFs are classified into three aspects: "improper handling by personnel", "ship equipment failure" and "poor environmental conditions".

(1) Improper handling by personnel

At present, the relevant operation norms and technical standards of ship to ship LNG bunkering are not clear enough, resulting in the professional quality of operators varying.

(2) Ship equipment failure

The communication, mooring and bunkering equipment of the LNG bunkering ship and the LNG powered ship are not kept in the best condition during the bunkering operation.

(3) Poor environmental conditions

Ship to ship LNG bunkering operations are often carried out in harbours, anchorages and other locations, with a high density of ships and a complex environment. The RIFs affecting the safety of ship to ship LNG bunkering operations are complicated.

On the basis of the above discussion, with reference to the ship to ship LNG bunkering fuel leakage fault tree constructed by the previous study (Lyu *et al.*, 2022), omitting the logical gate expressions and maintaining the hierarchical and indicator correspondence, the RIFs system is established as shown in **Table 2**.

TABLE 2. RIFs of fuel leakage during ship to ship LNG bunkering.

RIFs of level I	RIFs of level II	RIFs of level III
Improper handling by personnel	Simultaneous with other hazardous operations	Simultaneous barging operations
		Multi-ship bunkering operations
	Faulty bunkering operations	Personnel unwell
		Irregularities in pipe connections
		Poor operational cooperations
		Inadequate staff training
		Incomplete purge after bunkering

	Passing ships failing to avoid effectively	Absence without leave
		Failure to maintain a regular lookout
		Poor seamanship
Ship equipment failure	Mooring failure	Cable breakage
		Cable reel malfunction
		Bump pad offset
		Dragging anchor
	Breakage of bunkering equipment	Pipeline corrosion
		Wear loss at joints
		Overpressure of storage tanks
	Poor communication equipment	Unstable signal transmission
		Low battery on intercom
Poor environmental conditions	Poor weather and sea conditions	Excessive wind and waves
		Poor visibility
	Discomfort in the navigable environment	Heavy traffic flow
		Ship wave impact

Risk modelling based on FBRBN and ER

Risk parameters setting based on FMEA

Risk is a complex concept, which requires that risk assessments be carried out taking into account not only the likelihood of a catastrophic event occurring, but also the associated consequences. The RIFs of ship to ship LNG bunkering are intricate and coupled with each other, and it is unscientific to judge the risk only from the frequency of accidents. As a systematic approach, FMEA can identify known and potential failure models. Therefore, it is frequently utilised in reliability engineering as a powerful tool for assessing the potential failure risk level of a product. For example, Liu and Li (2021) proposed an enhanced FMEA model that takes into account the bounded rational behaviour of experts and expert group, so as to enable the investigation and analysis of potential failure mode risks of green logistics in cold chain; Shafiee and Animah (2022) put forward an integrated risk management framework which utilises the FMEA approach alongside a hybrid Multi-Criteria Decision Analysis model. The framework aims to evaluate risks and prioritise mitigation strategies for subsea facilities in high pressure/high temperature environments throughout their extended lifespan. To sum up, FMEA is one of the most popular risk assessment methodologies due to its visibility and ease of use (Yang and Wang, 2015). In this study, referring to the idea of FMEA, three risk parameters are set: the likelihood of occurrence (*L*), the severity of consequences (*C*), and the probability of non-detected risk (*P*). In order to achieve higher parameter identification, five evaluation levels are established for each risk parameter, the explanation of fuzzy variables corresponding to each evaluation level are shown in **Table 3**.

TABLE 3. Risk parameter evaluation grades and meanings.

Risk Parameters	Evaluation Grades	Fuzzy Variables
The likelihood of occurrence (*L*)	L_1	Very low
	L_2	Relatively low
	L_3	General
	L_4	Relatively high
	L_5	Very high
The severity of the consequences (*C*)	C_1	Can be ignored
	C_2	Not serious
	C_3	Medium
	C_4	Serious
	C_5	Disastrous
The probability of non-detection of risk (*P*)	P_1	Very unlikely
	P_2	Unlikely
	P_3	Normal
	P_4	More likely
	P_5	Very likely

Since the current practice of ship to ship LNG bunkering is still in its infancy, there is a lack of necessary data support for assessing the accident frequency in bunkering operations. Thus, an expert investigation method is adopted to conduct expert evaluation information consultation and investigation on RIFs of level III in **Table 2**. This survey invites 25 experts from maritime authorities, universities, and shipbuilding and operating companies. The job categories include managers, researchers, and operators with relevant operating experience of LNG onshore bunkering, ship to ship LNG bunkering, LNG loading and unloading and other navigation safety work. The experts have been engaged in research or practical application in the corresponding field for 5 years or more. The experts interviewed used a five-point Likert scale to express the belief level of RIFs, which sums to 1 for each RIFs value.

Reasoning of risk states based on FBRBN

In the survey to elicit expert opinion on RIFs, the uncertainty in the entire event is particularly acute. The main reasons include the ambiguity of the risk parameters defined by the semantic criteria, the incompleteness of the information data and the randomness of the assessment process. Therefore, when processing expert scoring data, uncertainty evaluation methods can be used to avoid reliance on accident data and to obtain more accurate assessment results.

The classical FMEA method has certain shortcomings, including inadequate quantification of the effectiveness of preventative measures (Cui *et al.*, 2023). To address these limitations, many new approaches including Markov model, grey theory, Bayesian network and fuzzy logic have been suggested (Xia *et al.*, Forthcoming). As an effective method in this study, BBN is utilized to depict the inference system between the input (L, C, and P) and output variable R (risk status) (Yang *et al.*, 2008). However, the subtle changes in linguistic variables within the antecedent attribute are not necessarily reflected in traditional Fuzzy Belief Rule (FBR) systems, due to the fact that their results are usually the result of a single output. In view of this, the ability of rule base to deal with uncertainty in a complex system can be improved by incorporating the notion of Belief Degree. For example, Wan *et al.*, (2019) introduced a new model for evaluating the RIFs of maritime supply chains, which utilises a fuzzy belief rule approach combined with BN. Yang *et al.*, (2009) proposed a subjective security-based assessment and management framework using fuzzy ER approaches by introducing the concept of degree of belief, which can be utilized to collate and analyze subjective risk assessment data pertaining to various aspects of a maritime transportation system from numerous experts in a systematic way. The regulations within the belief rule base are expressed by taking the shape of conditional probability to realize rule fusion. As a result, the new method can solve the problem of ambiguity and incompleteness effectively in uncertain systems by modelling the relationship between input conditions and output results, presenting the output results in the form of a belief distribution.

In this study, the experts use a five-point Likert scale to express the belief level of a risk parameter for each RIFs in level III, which sums to 1 for any risk parameter. In the meanwhile, risk parameters L, C, and P reflect different evaluation aspects of RIFs, and their weight differences largely affect the accuracy of quantitative evaluation of risk events. In view of the fact that there are few related studies in the field of risk assessment of ship to ship LNG bunkering, the same method of scoring by the interviewed experts is adopted to determine the weight of *L*, *C* and *P*. Each expert is given the same weight, i.e., an arithmetic mean is used to calculate the experts' scores for *L*, *C*, and *P*. After processing, the values of *L*, *C*, and *P* are determined as 0.18, 0.74, 0.08. Then there are 125 (5^3) rules in total for the FBR established in this study.

BN is one of the most effective conceptual networks for knowledge representation and inference research under uncertainty due to its advantages in expressing non-linear relationships (Cao *et al.*, 2023a). Thus, BN can be used to synthesize belief distributions for various rules. Therefore, through modelling of BN, the FBR base can be transformed in to a BN with several parent nodes and one sub-node. The information from the processed expert evaluations of the risk parameters can be used as the prior probability of each parent node, and the process of calculating the marginal probability of a sub-nodes is simplified by a belief rule-based risk inference process. On this basis, the marginal probability of sub-node can be obtained according to Eq. (1)

$$p(R_h) = \sum_{i=1}^{I} \sum_{j=1}^{J},...,\sum_{k=1}^{K} p(R_h \mid A_i, B_j, ..., C_k) p(A_i) p(B_j), ..., p(C_k) \qquad (1)$$

where *A*, *B* , . . . , *C* are the input conditions of the FBR; *I*, *J*, . . . , *K* are the number of reference values of each input condition; $p(A_i)$ is the probability that input condition *A* takes the i^{th} rank; $P(R_h)$ is the probability that risk state *R* is the h^{th} rank.

Aggregation of risk states based ER

In the survey on RIFs system conducted by the expert research method, only the scores of experts on RIFs in level III are collected due to the fact that the RIFs in level I and II are extensive and difficult to quantify. At this point, the risk data for levels I and II are missing, so it is necessary to deduce the risk status of the upper levels based on the risk status of level III, which is to complete the process of data aggregation. Before data aggregation, it is necessary to determine the weight of the RIFs in the upper level to the lower level.

Due to its extreme applicability, AHP is widely used in green port development evaluation (Wan *et al.*, 2018). For examples, Loughney *et al.*, (2021) utilized multi-attribute decision analysis and AHP methods to identify optimal locations for floating offshore wind farms along Scotland's northern coast; Yang *et al.*, (2018) investigate climate change adaptation measures in ports with high data uncertainty by combining fuzzy Bayesian risk analysis approaches, AHP and ER methods. AHP is proposed as a method for expressing and addressing individuals' subjective judgements in a quantitative form and is frequently implemented in making decisions involving multiple plans or objectives. Utilising the already established hierarchy of RIFs, the method makes use of less quantitative information in mathematising the decision-making process and serves as a potent technique for tackling intricate problems having multiple plans or objectives.

Table 2 expands the RIFs leading to ship to ship LNG bunkering fuel leakage in the form layers. The occurrence of lower-level RIFs will lead to the occurrence of upper-level RIFs, which will further lead to the occurrence of top incidents. The AHP method compares the lower-level RIFs contained in the upper level using a 1-9 scale method pairwise comparison, from this, the judgment matrix is constructed, so that the relative weight of the RIFs under a single criterion can be used to determine the weight of the indicators at different levels.

More recently, risk assessment of ship to ship LNG bunkering has seen a shift in research priorities. Due to the imprecise and incomplete nature of available data, the focus has moved from strictly quantifying probabilities and consequences to incorporating both accurate and uncertain information to better quantify risks (Ruponen *et al.*, 2022). During the process, the ER methodology has demonstrated its benefits in addressing incompleteness and uncertainties, especially in relation to Likert-based rating sets (Chang *et al.*, 2021). Combining AHP method, ER completes the aggregation of risk states by evaluating the results of RIFs at the lower level to obtain the risk states of RIFs at the upper level. The process is represented as follows:

The risk state of RIF A is assumed to be R_A, the risk state of RIF B is R_B, and the output risk state of both is R_{AB}, which can be obtained by aggregation. Each of the above 3 sets contains 5 levels, denoted as:

$$R_A = \left\{(R_1,\beta_A^1),(R_2,\beta_A^2),(R_3,\beta_A^3),(R_4,\beta_A^4),(R_5,\beta_A^5)\right\}$$

$$R_B = \left\{(R_1,\beta_B^1),(R_2,\beta_B^2),(R_3,\beta_B^3),(R_4,\beta_B^4),(R_5,\beta_B^5)\right\}$$

$$R_{AB} = \left\{(R_1,\beta^1),(R_2,\beta^2),(R_3,\beta^3),(R_4,\beta^4),(R_5,\beta^5)\right\}$$

where β is the distribution of belief levels for different levels of risk states.

During the risk assessment process, the normalised weights of RIFs A and B are called ω_A and ω_B $(\omega_A + \omega_B = 1)$. The weighted belief parameters M_A^m and M_B^m are defined by the data sets of R_A and R_B. Its expression is as shown in Eqs. (2) and (3).

$$M_A^m = \omega_A \beta_A^m \tag{2}$$

$$M_B^m = \omega_B \beta_B^m \tag{3}$$

where m is the number of risk status level (m = 1, 2, 3, 4, 5).

Assuming H_A and H_B as the belief levels not yet assigned to M_A^m and M_B^m, the expressions are shown in Eqs. (4) and (5).

$$H_A = \overline{H}_A + \tilde{H}_A \tag{4}$$

$$H_B = \overline{H}_B + \tilde{H}_B \tag{5}$$

where $\overline{H}_n (n = A, B)$ is the influence parameter for other RIFs; $\tilde{H}_n (n = A, B)$ is the information incompleteness parameter for R_A and R_B.

The relationship between the above parameters is expressed as Eqs. (6)-(9):

$$\overline{H}_A = 1 - \omega_A \tag{6}$$

$$\overline{H}_B = 1 - \omega_B \tag{7}$$

$$\tilde{H}_A = \omega_A \left(1 - \sum_{m=1}^{5} \beta_A^m\right) \tag{8}$$

$$\tilde{H}_B = \omega_B \left(1 - \sum_{m=1}^{5} \beta_B^m\right) \tag{9}$$

Then, the weighted belief parameter $\beta^{m'}$ after aggregation of R_A and R_B is calculated in Eq. (10):

$$\beta^{m'} = K(M_A^m M_B^m + M_A^m H_B + M_B^m H_A) \tag{10}$$

The incompleteness parameters after aggregation of R_A and R_B are calculated as Eqs. (11)-(12):

$$\overline{H}'_U = K(\overline{H}_A \overline{H}_B) \tag{11}$$

$$\tilde{H}'_U = K(\tilde{H}_A \tilde{H}_B + \tilde{H}_A \overline{H}_B + \tilde{H}_B \overline{H}_A) \tag{12}$$

where K is the normalization factor and its expression is shown as Eq. (13):

$$K = \left(1 - \sum_{s=1}^{5} \sum_{\substack{t=1 \\ t \neq s}}^{5} M_A^s M_B^t \right)^{-1} \tag{13}$$

At the end of the R_A and R_B aggregation operation, the new belief distribution of the original data is obtained by redistributing the belief levels in the incompleteness parameter $\overline{H}'_U$ to each level in the output risk state set, calculated in Eqs. (14)-(15):

$$\beta^m = \frac{\beta^{m'}}{1 - \overline{H}'_U} \tag{14}$$

$$H_U = \frac{\tilde{H}'_U}{1 - \overline{H}'_U} \tag{15}$$

In the Eqs. (14)-(15), β^m is the combined belief distribution of the aggregation results and H_U is the belief level of incompleteness of the aggregation process.

The above is the calculation process of aggregation of two pieces of evidence information. ER operation is in accordance with the law of exchange and the law of combination. When aggregating multiple risk state belief distribution data, any two aggregation can be performed first, and then the sequential operation is performed to finally get the aggregation results.

Quantification of RIFs

In order to translate the belief distribution of risk states into a numerical expression, the concept of utility values $U(R_h)$ is introduced and the utility values of the different levels of risk states are linearly assigned as: $U_{R1} = 1^3 = 1$, $UR2 = 2^3 = 8$, $U_{R3} = 3^3 = 27$, $U_{R4} = 4^3 = 64$, $U_{R5} = 5^3 = 125$.

The risk priority value index (*RPI*) can realise the quantification of RIFs, this process is realised by using the linear effect function. The specific calculation process is Eq. (16).

$$RPI = \sum_{h=1}^{5} p(R_h) \times U(R_h) \tag{16}$$

Validation

After finishing the modelling, it is crucial to verify its dependability. In this study, a sensitivity analysis of the results is performed using an axiom-based validation process. A reasonable model should satisfy the following 3 axioms (Wang *et al.*, 2023).

Axiom 1: Changing each parent node's prior probability will undeniably result in a proportional shift in its sub/target node's posterior probability.

Axiom 2: When the subjective probability distribution of the parent node changes, the degree to which different parent nodes influence the value of the sub-node ought to be commensurate with the weight of parent node.

Axiom 3: The impact of the set of risk parameters on *RPI* should always surpass the impact of alterations in any arbitrary subset on the *RPI* value.

Case study

Quantification of risk status

Zhoushan Port is one of the major port hubs in China, located in the north-east of Zhoushan Island. Xinao Zhoushan LNG receiving terminal is a comprehensive project that combines LNG storage and transshipment and ship bunkering with a number of other businesses and functions. Considering that it is located near an important shipping route between northern and southern China, comprehensive identification and quantification of bunkering risks can improve the quality of operators and build a risk prevention and control system to ensure operational safety.

In this section, the ship to ship LNG bunkering operation near the LNG emergency anchorage in Zhoushan is selected as the research object. A case study is conducted to apply the FBRBN, AHP and ER methods to develop an in-depth quantitative analysis of the RIFs leading to fuel leakage accidents during ship to ship LNG bunkering operations under uncertain conditions. It also can test the feasibility and practicality of the above research methods. Furthermore, a total of 25 experts, all from the field of ship to ship LNG bunkering and related fields, are invited to this study. The experts are invited to evaluate the Level III RIFs that contribute to fuel leakage in **Table 2**, using a Likert scale. The experts also scored the weights of *L*, *C*, *P* on a 1-9 scale for the lower-level RIFs contained in the upper level. In collating these three parts of the data, the same weights are given to the experts, i.e., the data are treated as arithmetic means.

After obtaining the belief ratings for the risk parameters from experts of the RIFs in Level III of the system, the experts are given the same weight in the process of combining their evaluations in order to reflect the generality of the data. Since L, C and P have 5 levels of evaluation, R is also divided into 5 levels from "very good" to "very poor" and is set from R_1 to R_5. Through equation (1), the risk states of the level III RIFs can be calculated. Taking the RIF "Cable reel malfunction" as an example, the value of the RIF is calculated:

$$p(R_h)= (13\%, 36\%, 24\%, 21\%, 6\%)$$

The result means there is a 13% probability of R_1, a 36% probability of R_2, a 24%probability of R_3, a 21% probability of R_4 and a 6% probability of R_5. The reasoning process can be demonstrated by using the Bayesian modeling software GeNIe 2.0, as shown in Figure 1.

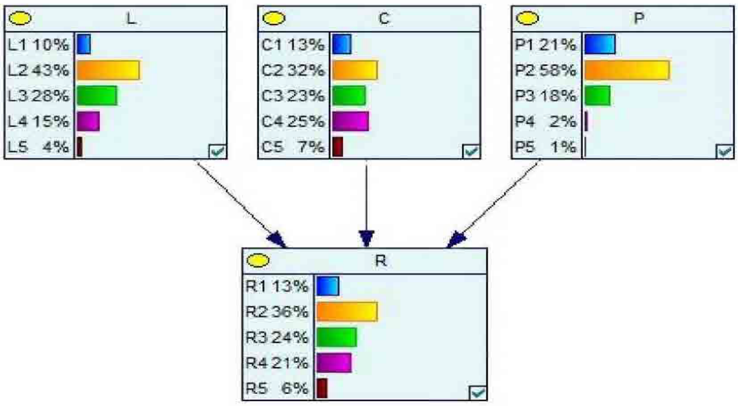

FIG. 1. Risk reasoning process on “mooring winch break down”

Likewise, the risk states of all RIFs from level III in the system can be obtained. This completes the reasoning of the bottom-level RIFs from risk states to risk parameters. In this expert research, AHP is used to collect the weight scores of experts on the RIFs of the lower-level included in the upper-level and complete the relevant calculations. A 1-9 scale is used to compare the RIFs on a two-by-two basis and to give importance assignments. This completes the calculation of the relative weight scores of the RIFs in level II and III of the system by different experts, and the evaluation results of the relative weights are also obtained in the form of arithmetic averages, as shown in **Table 4**.

TABLE 4. Relative weights of RIFs at level II and III.

RIFs of level II	Relative weights	RIFs of level III	Relative weights
Simultaneous with other hazardous operations	0.113	Simultaneous barging operations	0.208
		Multi-ship bunkering operations	0.792
Faulty bunkering operations	0.657	Personnel unwell	0.101
		Irregularities in pipe connection	0.397
		Poor operational cooperation	0.090
		Inadequate staff training	0.146
		Incomplete purge after bunkering	0.266
Passing ships failing to yield effectively	0.230	Absence without leave	0.560
		Failure to maintain a regular lookout	0.328
		Poor seamanship	0.112
Mooring failure	0.312	Cable breakage	0.311
		Cable reel malfunction	0.174
		Bump pad offset	0.177
		Dragging anchor	0.338
Breakage of bunkering equipment	0.586	Pipeline corrosion	0.120
		Wear loss at joints	0.278
		Overpressure of storage tanks	0.602
Poor communication equipment	0.102	Unstable signal transmission	0.357
		Low battery on intercorn	0.643
Poor weather and sea conditions	0.617	Excessive wind and waves	0.567
		Poor visibility	0.433
Discomfort in the navigable environment	0.383	Heavy traffic flow	0.483
		Ship wave impact	0.517

And then, the risk states of all RIFs in the system level I and level II are obtained using the evidential reasoning method. Finally, using equation (16), the quantification of the risk status of all RIFs in the system is completed, as shown in **Table 5**.

TABLE 5. Comprehensive sequencing of fuel leakage RIFs during ship to ship LNG bunkering.

RIFs of level I	RPI	Rank	RIFs of level II	RPI	Rank	RIFs of level III	RPI	Rank
Improper handing by personnel	69.84	1	Faulty bunkering operations	71.10	1	Inadequate staff training	89.48	1
						Personnel unwell	79.95	2
						Irregularities in the pipe connections	76.50	3
						Poor operational cooperations	58.28	8
						Incomplete purge after bunkering	44.61	13
			Passing ships failing to avoid effectively	64.04	2	Absence without leave	66.38	4
						Failure to maintain a regular lookout	60.27	6
						Poor seamanship	38.66	16
			Simultaneous with other hazardous operations	55.26	4	Multi-ship bunkering operations	55.07	9
						Simultaneous barging operations	49.19	10
Poor environmental conditions	56.66	2	Poor weather and sea conditions	61.69	3	Excessive winds and waves	62.49	5
						Poor visibility	59.33	7
			Discomfort in the navigable environment	42.87	5	ship wave impact	48.54	11
						Heavy traffic flow	37.47	17
Ship equipment failure	38.90	3	Breakage of bunkering equipment	42.17	6	Wear loss at joints	47.71	12
						Overpressure of storage tank	42.03	14
						Pipeline corrosion	29.40	21
			Mooring failure	34.83	7	Cable breakage	40.88	15
						Dragging anchor	37.08	18
						Cable reel malfunction	30.43	20
						Bump pad offset	24.67	22
			Poor communication equipment	27.72	8	Low battery on intercom	31.88	19
						Unstable signal transmission	19.26	23

Validation

The three axioms in section Validation above will be applied to validate the robustness of the model in the risk assessment of ship to ship LNG bunkering. Taking the RIF "Cable reel malfunction" as an example, in order to avoid possible deviations due to expert judgement and missing data, the findings from the model analysis are compared to verify the correctness and validity of the model developed.

In this case, there is a positive correlation between the *RPI* value of the RIF and the probability values of the three risk parameters. For example, the closer the likelihood of occurrence L is to "very high L_5", the closer the severity of consequences C is to "disastrous C_5", the closer the probability of non-detection risk P is to "very likely P_5", the closer the risk status R is to "very poor R_5", and the higher the *RPI* value of the RIF is. In the RIF "cable reel malfunction", for likelihood of occurrence L, the subjective probability of 0.1 is redistributed to different levels on the basis of the original model in a way that maximises the increase in the *RPI* value. When the subjective probability of L_1 decreases by 0.1 and the subjective probability of L_5 increases by 0.1, the *RPI* value increases from 30.43 to 32.91. The process of testing the severity of consequences C and probability of non-detection risk P is the same. Such an analytical approach is applied to other RIFs at the level III of system to examine the impact of changes in subjective probability distributions of any of the three risk parameters on the *RPI* values. The results are in accordance with axiom 1. No outliers in the magnitude of change in *RPI* values, which indicates that the FBRBN methodology used in the present case has strong logic and consistency.

The above test results demonstrate the sensitivity of the model to discrete changes. Similarly, it is necessary to carry out a sensitivity analysis of continuous changes. For each risk parameter, the subjective probability of 0.02 is reallocated each time with the largest increase in the *RPI* value. The incremental change in the *RPI* value is examined for the subjective probability of change interval in the incremental process of [0, 0.1]. Taking RIF "cable reel malfunction" as an example, the calculation results are shown in Figure 2. It can be seen by comparison that the degree of influence of changes in the probability values of different risk parameters on the *RPI* value is significantly different. But, the degree of influence is always proportional to the weights of the three risk parameters *L*, *C* and *P* (*L*: *C*: *P* = 0.18: 0.74: 0.08). Similarly, the other RIFs at level III are all in line with the above regular characteristics. Therefore, the test results are in line with axiom (2), indicating that the FBRBN method used in this case has good robustness.

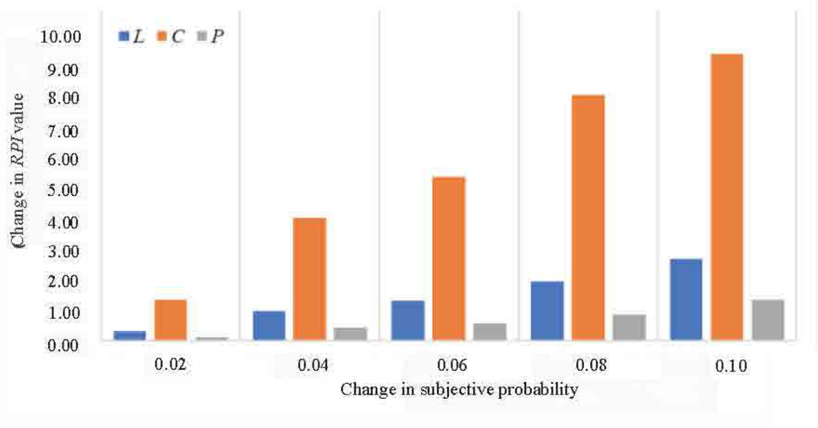

FIG.2.Sensitivity analysis on the influence of various probability value of risk parameters

Finally, the effect of combinations of changes in the probability values of the risk parameters on the *RPI* values is examined by dividing the three risk parameters into seven possible combinations. The number of risk parameters for reallocating subjective probabilities are 1,2 and 3 respectively, category 1 considers only the change in the probability value of one risk parameter. Category 2 considers the combinations of the changes in the probability values of the two risk parameters. Category 3 considers the change in the probability values of all the three risk parameters in the third category. Still taking the RIF "cable reel malfunction" as an example, for each risk parameter, the subjective probability of 0.1 is redistributed in different classes in the way to increase *RPI* value the most, and the corresponding results of the change in *RPI* value are shown in **Table 6**.

TABLE 6. The influence of various risk parameter combinations on *RPI*.

Portfolios	Risk parameter			RPI value	Amount of RPI change
	L	*C*	*P*		
#1	O			32.91	2.48
#2		O		39.11	8.68
#3			O	31.67	1.24
#4	O	O		41.59	11.16

#5	O		O	34.15	3.72
#6		O	O	40.35	9.92
#7	O	O	O	42.83	12.40

“O” denotes the selection of items for different combinations of risk parameter variations.

By comparing the data in the **Table 6**, it is possible to determine the relationship between the magnitude of the effect of the varying combinations of probability values of different risk parameters on the *RPI* values. Taking portfolio #4 as an example, the amount of changing *RPI* value corresponding to this portfolio is 11.16 (41.59-30.43). The subsets of this portfolio are portfolio #1 and #2 respectively, with the amount of change in *RPI* value 2.48 (32.91-30.43) and 8.68 (39.11-30.43) respectively, which is less than 11.16, and conforms to axiom (3). Similarly, comparative analyses can be carried out between other RIFs and other combinations of the level III RIFs, and the results of the tests are all in accordance with axiom (3), indicating that the FBRBN method used in this case is sufficiently reliable and reasonable.

Analysis of results

It can be seen from **Table 5** that the comprehensive risk degree of RIFs of ship to ship LNG bunkering fuel leakage level I in this case is "improper handling by personnel", "poor environmental conditions" and "ship equipment failure". Based on the above three aspects, this study conducts an in-depth analysis of RIFs with high *RPI* values, explores the causes of the problem, and proposes corresponding security measures.

The RIF with the highest risk priority in level I is "Personnel Unwell", which has the highest *RPI* of 69.84. Among the level III of RIFs, the *RPI* values of "inadequate staff training", "personnel unwell", "irregularities in pipe connections" are as high as 89.48, 79.95, and 76.50, ranking the top 3 RIFs and are the main RIFs affecting the safety of ship to ship LNG bunkering. And these RIFs all belong to the level II RIF "Faulty bunkering operations". This is because the ship to ship LNG bunkering operation is still in its infancy, and the training of operators and related technical standards are not perfect. Therefore, the training and assessment of the staff engaged in ship to ship LNG bunkering operation should be strengthened. A rigorous selection and elimination mechanism should be set up to select crew members with high professionalism to be in charge of the operation. Relevant training departments should fully understand the high risk of ship to ship LNG bunkering operation to optimise the theoretical curriculum and practical assessment mode. Law enforcement departments should also strengthen inspection and supervision. Meanwhile, if the operator is found to be physically incapable of fulfilling the job requirements, the bunkering operation should be stopped immediately and a suitable replacement should be arranged. The LNG bunkering ship and the LNG-powered ship should make sure that both sides can accurately understand each other's division of labours, so as to perform their respective duties and work closely together.

Poor environmental conditions in level I have the second highest *RPI* value of 56.66. The *RPI* values for excessive wind and waves and poor visibility are relatively high, which are also classified as severe weather and sea conditions in level II. This is due to the climate characteristics of Zhoushan sea area: Zhoushan harbour has abundant rainfall. During the fishing moratorium, there will be occasional bad weather and sea conditions such as sea fog, thunderstorms and even typhoons. Thus, the natural environmental conditions need to be paid more attention. In the process of ship to ship LNG bunkering operation, both the bunkering ship and the recipient ship should do:

Ships need to pay attention to the natural environmental conditions in real time and make early prediction. The weather forecast or weather fax map issued by the weather station in time need to be received to make all preparations. If it is found that the operation area is about to encounter or is encountering the catastrophic weather such as "excessive wind and waves", the operation should be stopped immediately and take effective collision avoidance measures decisively.

Bunkering operations in "poor visibility" conditions should correctly display lights according to the regulations of the sound horn. Operators should closely observe the changes in the farthest visibility distance. Radar, VHF, AIS and other navigational aids need to be used correctly, crew also need be aware of ship dynamics in time. If it is necessary, crew should timely report to the VTS centre and seek the assistance of maritime management agencies to implement traffic control.

Ship equipment failure in level I has the lowest *RPI* value of 38.90. Among them, the *RPI* values of “unstable signal transmission”, “Bump pad offset”, and “pipeline corrosion” are the lowest, indicating that their comprehensive impact on the safety of ship to ship LNG bunkering is relatively small. This is also related to the fact that both LNG bunkering ships and LNG powered ships meet relatively high design standards. Therefore, it is important for operators to enhance equipment and maintenance and for maritime administrations to implement rigorous inspection regimes and standards.

This study will help to improve the safety level of ship to ship LNG bunkering operations, and provide reference for stakeholders in the formulation of relevant technical standards and regulations, etc. At the theoretical level, based on the consideration of the impact of uncertainty on the safety assessment of ship to ship LNG bunkering, this study innovatively introduces a system to identify factors that affect the safety of ship to ship LNG bunkering operation and finally realises quantitative risk assessment. At the practical level, the numerical value and ranking of *RPI* in this study can help stakeholders understand the impact of different operating entities and RIFs on operating safety. This study also provides targeted recommendations for different RIFs. In view of this, in the practice of ship to ship LNG bunkering operations in the future, it is necessary to standardize the operational behavior of personnel, closely monitor environmental changes, and strengthen equipment maintenance.

Conclusion

This paper proposes a new evaluation approach for the identification, quantification and ranking of ship to ship LNG bunkering RIFs. On the basis of relevant research, a risk assessment model for quantitatively ranking risk events using FMEA, AHP, FBRBN and ER methods is proposed. As a result, reasoning from risk parameters to risk states for specific RIFs under uncertainty, aggregation operations for risk states and quantitative ranking of risk values are implemented. The results of the study show that "improper handling by personnel" is the most important RIFs affecting the safety of ship to ship LNG bunkering. Among them, "inadequate staff training", "personnel unwell" and "poor operational cooperation" are the three RIFs with the highest *RPI* in the level III of the system. This study validates the efficacy of the model through a case study. The results indicate a high level of robustness and practicality of the proposed risk assessment model.

However, due to the incompleteness caused by the lack of relevant cases, the ambiguity of expert evaluation opinions, and the randomness of the operating environment, the limitations of this study still exist. Due to the limited number of accident reports collected in this study, the interactions between the RIFs are not investigated. In future research, the objective data collected in actual work cases can be used to replace some of the expert scoring data in the research process of this paper, so as to further improve the credibility and practicability of the relevant models.

Data Availability Statement

The following data supporting the results of this study are available from the corresponding author upon reasonable request.

(1) Fuzzy belief rule base for ship to ship LNG bunkering fuel leakage risk evaluation.

(2) Weighting evaluation and subjective probability evaluation of the processed risk factors from the ship to ship LNG bunkering fuel spill questionnaire.

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