Guo, Y, Jin, Y, Hu, S, Yang, Z, Xi, Y and Han, B

Risk evolution analysis of ship pilotage operation by an integrated model of FRAM and DBN

Reliability Engineering and System Safety 229 (2023) 108850

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Risk evolution analysis of ship pilotage operation by an integrated model of FRAM and DBN

Yunlong Guo [a,b], Yongxing Jin [a], Shenping Hu [a,*], Zaili Yang [c,*], Yongtao Xi [a], Bing Han [d]

[a] Merchant Marine College, Shanghai Maritime University, Shanghai 201306, China
[b] School of Nautical Technology, Jiangsu Shipping College, Nantong 226010, China
[c] Liverpool Logistics Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool L3 3AF, UK
[d] Shanghai Ship and Shipping Research Institute, Shanghai 200135, China

ARTICLE INFO

Keywords:
Risk evolution
FRAM
DBN
Markov model
Ship pilotage
Maritime risk

ABSTRACT

The risks involved in ship pilotage operations are characterized by random, uncertain and complex features. To reveal the spatiotemporal evolution of ship collision risks in the pilotage operations process, a risk evolution analysis model is developed in this paper by the combination of a Functional Resonance Analysis Method (FRAM) and Dynamic Bayesian Network (DBN). First, based on the analysis results of the functional resonance mechanism of a ship pilotage system, the relevant collision risk influencing factors (RIFs) and their coupling relationships are identified. Second, the DBN is quantified by the employment of various uncertainty treatment methods including the Dempster-Shafer evidence theory for the configuration of the prior probabilities and a Markov model for the dynamic factors' transition probability calculation. Finally, using the temporal observation data, the temporal risk inference is conducted to reveal the risk evolution law in a ship pilotage operations process. The findings show that the evolution of collision risk in ship pilotage is significantly sensitive to regional locations, resulting in a "U" curve shaped by the action of functional resonance. "Inadequate human look-out" is among the most influential factors, and hence targeted risk control strategies should be formulated to ensure the safety of ship pilotage operations.

1. Introduction

The shipping industry is deemed as the lifeline of ensuring global economic development. With an incomparable cost advantage in the transport of long-distance bulk cargo, it represents 90% of the freight volume in international trade [1]. Although showing attractiveness, it renders a high risk that leads to catastrophic consequence such as loss of life, damage to property and environment, particularly in constraint waters (e.g. ports and canals/channels). Ship pilotage is implemented compulsorily (in many countries) to undertake the tasks such as ship navigation and berthing/unberthing and to ensure ship safety in port [2]. However, due to the complexity of navigation environment in port waters and intensive traffic, the safety of ship pilotage still faces great uncertainty, resulting in the occurrence of accidents [3]. According to the pilot-related ship accident reports published by International Group of P&I Clubs, ship collisions account for more than 50% of nautical accidents [4]. Despite the relevant high collision risk it exposes, pilotage operations attract less safety-related research compared to other maritime operations, requiring new studies to address this problem with urgency.

Due to the complex and changeable hydrological environment and the frequent convergence of ships in port waters, the complex interaction between the human-ship system and the environment is unavailable, leading to a great collision risk during ship navigation [5]. On the basis of International Regulations for Preventing Collisions at Sea (COLREGS), all the International Maritime Organization (IMO) member states have formulated the regulations for ship collision avoidance in inland waters and pilotage management regulations among the others [6]. The maritime administration adopts a Vessel Traffic Service (VTS) mode with the help of radar, and Automatic Identification System (AIS) to strengthen the navigation safety of ships in port waters. Along with the above-mentioned regulations, ship collision risk studies have been conducted from multiple perspectives in the existing literature. However, the studies on ship collisions in pilotage operations are scanty, and significantly less than those relating to the ship operations at open waters. It is even more worrisome when an increase of ship collisions and

* Corresponding authors.
E-mail addresses: sphu@shmtu.edu.cn (S. Hu), z.yang@ljmu.ac.uk (Z. Yang).

https://doi.org/10.1016/j.ress.2022.108850
Received 30 May 2022; Received in revised form 14 September 2022; Accepted 18 September 2022
Available online 19 September 2022

contacts accidents occur in seaports.

Aiming at analysing the complex coupling and dynamic evolution characteristics in ship pilotage operations risk, this paper pioneers the combination of a Functional Resonance Analysis Method (FRAM) and Dynamic Bayesian Network (DBN) to analyze the functional resonance and identify the collision risk in a ship pilotage process based on specific operations scenario analysis. The DBN model is used to combine expert knowledge, historical data and observational data to infer the spatio-temporal evolution law of ship collision risk in a specific pilotage scenario.

The remainder of this paper is organized as follows. The state-of-the-art of the maritime risk research literature is reviewed with a focus on ship collisions in Section 2, and it aids to reveal the weaknesses of the existing studies and formulate the research problems. In Section 3, a risk evolution analysis framework is proposed for ship pilotage operations by integrating FRAM and DBN. In Section 4, a case study of collision risk evolution analysis during container ship pilotage operations is conducted to verify the feasibility of the proposed method. Section 5 discusses the research method and results, and Section 6 is the conclusion of this paper.

2. Literature review

This section is outlined in five sections, including the literature relating to maritime risk analysis, the developments of BN, FRAM and DBN in maritime risk studies, respectively before the introduction of the new contributions in the last section.

2.1. Maritime risk analysis and risk evolution analysis

Maritime risk analysis is one of the effective and important ways to enhance maritime safety. The IMO accepts and advocates the Formal Safety Assessment (FSA) method proposed by the UK Maritime & Coastguard Agency (MCA), with a fundamental aim to evaluate the regulatory changes and/or make a comparison between the existing and possibly improved regulations, with a view to achieving a balance between the various technical and operational issues [7,8]. Traditional maritime risk analysis methods have been developed and applied with regards to the framework of FSA, using qualitative, semi-quantitative or quantitative methods [9] to integrate the probability and consequence of accident for capturing the magnitude of risk. Although the FSA has been widely used in maritime risk analysis, it still has some deficiencies, and its application is also under continuous development [10]. The identification of risk influencing factors (RIFs) for ship accidents is the basis for maritime risk analysis, which is generally obtained through historical data analysis or expert judgment [11]. With the development of maritime technology and safety management, the composition and mechanism of RIFs are also variational. Ship accident surveys and studies show that more than 80% of ship accidents are related to human and organizational factors [12], therefore, they have received extensive attention and research by relevant scholars [13]. Human Factor Analysis and Classification System (HFACS) is a comprehensive human error analysis method based on the Reason model, and is currently among the most popular human factor identification and modeling methods [14]. As the second generation of human reliability analysis method, Cognitive Reliability Error Analysis Method (CREAM) is mostly used in combination with other quantitative analysis methods for human error probability quantification [15]. Wu et al. [16] reviewed the methods and technologies of human and organizational factors in maritime risk analysis, and pointed out that the development of autonomous ships brought new changes and challenges to maritime risk analysis. As the future direction and research hotspot of intelligent shipping, an important contribution of maritime autonomous surface ship (MASS) is to reduce the impact of human factors on ship safety through the use of intelligent technology [17], although it might brought new types of risks such as cyberattacks [18]. However, in different stages of the development of ship autonomy, human factors still have an important impact. MASS is also affected by human factors, natural environment and traffic conditions during the encounter with conventional ships, various RIFs need to be comprehensively considered in the maritime risk analysis [17].

Accident causation theories are accident mechanisms and models extracted from a large number of accidents, and are widely used in maritime risk analysis. Early risk analysis methods are mainly developed based on the domino model [11], which is a typical linear causal secondary theory. With the deepening of safety research, researchers began to consider multiple sequences and potential conditions of failure events, followed by the emergence of risk analysis methods based on epidemiological models [19]. However, the risk analysis methods based on an epidemiological model still imply the linear thinking of sequence and causality. In order to overcome this deficiency, various systems-based risk analysis methods such as accident map (AcciMap), System-Theoretic Accident Model and Process (STAMP) and FRAM have successively appeared [20]. de Linhares et al. [21] used STAMP, FRAM and Resilience Assessment Grid (RAG) for the same accident analysis and comparison, and proposed these three approaches may be used together in a phased manner in risk analysis of complex sociotechnical systems. Wróbel et al. [22] built a collision avoidance process model based on STAMP, and then combined accident analysis and expert knowledge to evaluate the effect of specific collision avoidance actions.

The maritime risk research under the FSA framework is mainly aimed at the quantitative analysis of macro static risk, in order to realize the precise control of the ship operation process risks. It means that the research on the operation risks of individual ship in different scenarios has become a major issue [23]. The RIFs and their states of individual ships in different operation scenarios are often different. Therefore, the identification and analysis of RIFs need to consider not only specific scenarios such as their operation environment, ship characteristics and operator factors, but also the temporal and spatial characteristics of RIFs. In order to conduct a comprehensive analysis of the navigation risk of MASS, Fan et al. [13] referred to relevant literature and used expert knowledge to identify the RIFs of MASS in four operational stages from four aspects: human, ship, technology, and environment. Based on the identification of the main operational hazards of MASS by Failure Mode and Effects Analysis (FMEA), Chang et al. [17] combined with Evidential Reasoning (ER) and Rule-based Bayesian Network (RBN) to quantitatively evaluate the risk level caused by the identified hazards. Based on 10 years AIS data learning, Gil et al. [24] obtained the influencing factors of the Bow Crossing Range (BCR) and the empirical safety value of BCR where various ships encountered in different scenarios. In addition, with the development of the Arctic waterway, the safety of individual ship navigation in the Arctic waters has received major attention. Considering the influence of special scenario factors such as ice, severe operating conditions, and unpredictable climatic changes, relevant scholars have studied the individual ship accident risks of ship besetting [25], ship-ice collision [26], ship-ship collision [14] and grounding [27] in Arctic waters. In order to quantitatively analyze the overall risk probability of individual ship navigation process, Yu et al. [23] considered not only the influence of static factors such as ship characteristics, but also dynamic geometric risk factors related to local traffic factors. Yu et al. [28] identified the RIFs of navigation and natural environment from the perspective of geometric risk, and used Bayesian Network (BN) modeling to evaluate the spatial and temporal distribution of ship and offshore installation collision risk in real scenarios.

As the research on the risk of individual ship operation process gradually attracts the attention of scholars, the coupling correlation and dynamic characteristics of RIFs and the analysis of operation scenarios have become emerging. Hu et al. [29] used STAMP to model the risk evolution structure of LNG-fueled vessel system, combined with genetic algorithm (GA) and a cloud model to simulate the risk evolution process of LNG-fueled vessel during specific navigation. Xuan et al. [30] proposed a complete node model based on the risk analysis of LNG bunkering operations, established a system dynamics model based on the catastrophe theory, and simulated the risk evolution of a ship bunkering process. Li et al. [31] built a DBN model together with the Dempster-Shafer (D-S) evidence theory and cloud models to integrate expert judgment, marine meteorological data, and monitoring data to infer the risk evolution of an LNG vessel running in arctic waters. With the complex coupling of the environment, ship equipment and operators in a ship pilotage operations process [3], the system risk performance presents a spatiotemporal change, that is, the risk evolution of the operation process. New studies to capture such risk evolution of ship pilotage operations are needed in order to obtain the insights for the rational safety management more effectively.

2.2. Maritime risk analysis using BN and DBN

As a probabilistic graphical model, BN can quantitatively represent the coupling relationship between RIFs [23], and effectively synthesize subjective and objective data with uncertainty for risk inference. In this process, the RIFs and inference results can also be updated with new observations [32]. Maritime risk analysis by establishing a BN model includes two critical issues, the determination of BN structure and parameter quantification. The common method to determine the BN structure is to build it based on historical accident data learning or expert judgement [33]. Liu et al. [34] used a large amount of Port State Control (PSC) inspection data to build a BN model through a data-driven structure learning algorithm and used it for the analysis of ship detention risk. Jiang et al. [35] used the K2 algorithm and expectation-maximization to learn the network structure and conditional probability table (CPT) of BN from accident data, respectively. Özaydın et al. [36] built a BN structure according to expert advice, and learnt the CPT of BN nodes from accident data, then used a predictive Apriori algorithm to determine the minimum requirements required for the occurrence of occupational accidents. In order to reduce the uncertainty caused by expert judgment when the accident data is insufficient, Li et al. [37] used a binary logistic regression method to obtain the prior probability (PP) input of BN nodes using various data resources. However, historical data is often scarce, and it has become a common practice to map other risk analysis models to BN, among which Fault Tree Analysis (FTA), Event Tree Analysis (ETA), and Bow-Tie (BT) [38] play a dominant role. However, for the BN model of individual ship navigation risk assessment, the risk analysis based on historical data cannot often capture the real scenario risk, and it is necessary to use systematic risk analysis methods to characterize the risks of specific operating scenarios. Chaal et al. [39] adopted System Theoretic Process Analysis (STPA) for hazard analysis and the identification of Risk Control Options (RCOs) for autonomous ships, while BN was employed in the framework for estimating the system risk. Qiao et al. [40] used FRAM to construct a BN structure based on the qualitative description of an emergency response process, and employed an improved K-shell decomposition algorithm to obtain the PP of BN. Fu et al. [41] constructed an AcciMap model to describe the relationship between RIFs and mapped it to BN for quantitative analysis of ship grounding risk.

As the main parameters of a BN model, PP and CPT are mainly obtained through historical data learning or expert judgment. Ung [42] obtained the PP and CPT of a BN model based on 5 years of accident data combined with a mapping process contemplating the states from parent nodes. When historical data is incomplete, expert knowledge is often used to obtain BN parameters [27]. In order to prevent the knowledge limitation of experts, Yang et al. [15] adopted an ER method to fuse different expert judgments and to obtain the CPTs of the BN model for Human Error Probability (HEP) inference. In order to solve the problem of insufficient and incomplete data, Pan et al. [43] combined fuzzy function and an improved D-S evidence theory to fuse multiple experts to get the fuzzy PP of each risk factor, and then use it into the BN model to achieve risk inference. In addition, according to the mutation characteristics of environmental RIFs during a ship navigation process, the monitoring data of AIS, radar and other equipment are used to provide an important data source for the parameterization of BN [23]. Although showing some attractiveness, previous relevant studies fail to model RIFs in BN in terms of their temporal changes during individual ship pilotage operation process. The conventional BN has the limitations in dealing with the dynamic characteristics of RIFs and inference of temporal risk. Therefore, it is necessary to introduce DBN for temporal dynamic risk research.

DBN [44] as an extension of BN in time series, combines the advantages of BN and Markov chain (MC) to effectively deal with dynamic risk inference problems under multi-factors associations. Dabrowski and Villiers [45] constructed a DBN model of maritime piracy situation based on a switching linear dynamic system analysis, then simulated the spatiotemporal evolution of various vessels behavior of maritime piracy. Li et al. [46] constructed the MC based on observation data to obtain the state transition probabilities of the dynamic factors in a DBN, to realize the reasoning of the temporal risk evolution of a ship navigation process in the Arctic waters. Khan et al. [26] constructed a DBN model of ship-ice collision risk by considering the influence of objective factors such as visibility, ice condition and ship speed on an Arctic route. Based on the observation hypothesis of multi-step transfer of dynamic RIFs states, temporal risk evolution inference of ship-ice collision in a navigation process was carried out. Qian et al. [44] evaluated the dynamic natural environment risk of the key nodes in the Arctic Northwest Passage by constructing a DBN through index selection and data processing under a ship navigation scenario. DBN can synthesize observational data, expert knowledge and simulation data, and combine the transition probabilities of dynamic factors to realize the temporal inference of system risk [31]. It is revealed that DBN is suitable to the inference of risk evolution in ship operations. The accuracy of the risk evolution inference result using DBN depends not only on the rationality of the network structure, but also on the validity of the dynamic nodes transition probability. It is common to use observation data, simulation data, expert knowledge and MC model in a holistic way to obtain the effective transition probabilities of DBN dynamic nodes [47]. However, such applications and studies have yet been witnessed in a ship pilot operation.

2.3. Applications and development of FRAM in risk analysis

As a system analysis method, FRAM emphasizes that accidents and risk factors of dynamic systems should be analyzed from the perspective of the functional characteristics of system operations [48]. It has been continuously developed from its creation in 2004 and is widely used in accident analysis and/or risk assessment of complex socio-technical systems across different sectors, such as aviation [49] and maritime operations (Patriarca, 2017). Patriarca et al. [50] systematically reviewed the state-of-the-art of FRAM from a methodological aspect, application domains, and potential future research directions. As a typical socio-technical system, the FRAM method can aid to identify scenario-based risk factors and their complex coupling relationships in a ship operations process. Salihoglu and Beşikçi [51] used FRAM to qualitatively analyze the Prestige oil spill accident, and effectively identify the key functions and internal influencing factors affecting the accident, revealing the outstanding advantages of FRAM in the analysis of maritime accidents. Through the identification and description of the main functions of fishing expeditions, the analysis of functional variability and coupling between functions was carried out, and the safe operation path under functional aggregation was explored, to improve safety in artisanal fishing [52]. Although the FRAM method can reveal the functional coupling and risk emergence mechanism of complex socio-technical systems, the process of identifying and describing functions often relies on the subjective judgment of experts and lacks effective consistency and normative. In addition, as a qualitative analysis method, there are shortcomings in terms of the provision of a quantitative risk analysis result, and it needs to be combined with other methods to expand the application.

Accident Causation Analysis and Taxonomy (ACAT) is an accident analysis method based on STAMP. It based on both system safety and control theories assumes that any complex system is regarded as a control system composed of actuator, sensor, controller, and communication which are coordinated together to make the system work smoothly and continuously [53]. As a risk analysis method, ACAT defines the system from two aspects: structural decomposition and functional abstraction. An ACAT model may be used to enrich FRAM by establishing a hybrid FRAM-ACAT framework, in which operations process can be divided into subtasks, so the inter-level functions can be defined based on subtasks. For each inter-level function, three intra-level functions are further identified to ensure the completion of the subtasks. Thereby more functional constraints and deep contributing factors to operational risk can be identified with the hybrid approach [54].

In view of the insufficiency of the quantitative analysis of FRAM, scholars have combined it with other methods to improve the FRAM to realize its quantitative or semi-quantitative research. Patriarca et al. [55] proposed a semi-quantitative analysis framework of FRAM based on Monte Carlo simulation, considering the response of the system to different operation conditions and different risk states, and applied it for semi-quantitative security assessment of an Air Traffic Management (ATM) system. Kaya et al. [56] combined FRAM with Monte Carlo simulation and critical matrix methods to model tram operating systems and identify critical couplings and risks threatening system safety through semi-quantitative evaluation. Yu et al. [57] developed a data-driven method to quantify functional coupling relationships using the elevated confidence intervals of association rules, and to identify the paths of potential dangerous scenarios through the merging of association rules. Qiao et al. [40] combined FRAM, a directed complex network and BN in a novel model to evaluate the resilience involved in maritime liquid cargo emergency response. It takes advantages of the probabilistic reasoning ability of BN, to effectively address the deficiency of FRAM quantitative analysis. Zinetullina et al. [58] proposed an integrated method of FRAM and DBN for quantitative resilience assessment of chemical process systems. Therefore, FRAM can realize quantitative research on dynamic risk evolution supplemented by other quantitative analysis methods based on the analysis of the coupling mechanism of risk factors in the operation system.

2.4. DBN in safety systems of a high coupling feature

Due to the outstanding advantages of DBN in dealing with the coupling relationship of system factors, temporal dependence and information uncertainty, it is widely used in reliability analysis, dynamic risk analysis, and resilience assessment of operations process of a high coupling feature such as deepwater drilling operation, emergency operations and construction equipment operation. Špačková and Straub [59] considered the random dependencies of human factors and other external factors, and carried out probabilistic assessment of tunnel construction performance by constructing a DBN model based on an improved Frontier algorithm. Guo et al. [60] combined the fuzzy set theory with DBN to propose a fuzzy DBN method that used triangular fuzzy numbers to preserve uncertainty information, to improve the ability of dynamic risk assessment methods. Li et al. [61] proposed an analysis model to analyze the hazard perception error (HPE) of construction equipment operators by combining a cognitive model and DBN. It was used to determine the conditional probability distribution of DBN through a key cognitive function calculation model and multi-source information synthesis. Zhang et al. [62] proposed a resilience evaluation method by combining DBN and a finite element model, and evaluated the temporal dynamic resilience of subsea wellhead connector from two aspects of degradation process and recovery process. The literature of DBN in safety analysis shows that the effective acquisition of the PP, CPT and transition probabilities of dynamic nodes in a DBN is the key to realize effective inference of temporal risk. DBN parameters need to be obtained according to scenario analysis, combined with simulation data, observation data, a Markov model, historical data and expert judgment [47]. As a scenario risk, the individual ship pilotage operations process risk is highly dynamic and uncertain. It needs to rely more on scenario observation data and expert knowledge to obtain the input parameters of the model, and to realize the effective inference of risk evolution. It is therefore chosen as a key supporting technique in the newly developed methodology in Section 3.

2.5. New contributions

The literature review in the above sections shows that the research on ship collision risk focuses on the identification of collision-related RIFs and the analysis of ship operability. In the process of ship pilotage operations, the performance of ship collision RIFs will lead to changes in the safety behavior of ships during their navigation process. It presents a major research challenge on the evolution analysis of ship pilotage risk, as well as the understanding of random variables and random phenomena that are caused by the change of risk factors. This paper pioneers a Markov hypothesis to promote the development of risk assessment in the operations process of ship pilotage. Based on the network topology relationship of ship collision risk factors, a DBN model is established by a new approach through which the description of subjective and objective data collection, the development of the Markov chain hypothesis, the transition matrix of risk factors on random phenomena, and the capture of temporal risk characteristics are combined holistically under the time sequence within the context of ship pilotage operations. The combination of FRAM and ACAT introduced into the field of safety research has been first witnessed from the perspective of describing operation process risks. Furthermore, ship pilotage operations are described in the functional resonance model of ship behavior for the first time, which can be tailored and generalized to model the operation process risk of similar features in the other sectors.

3. Methodology

This section proposes a novel hybrid approach of FRAM and DBN with new data from both objective sources and subjective judgement to analyze collision risk evolution characteristics of ship pilotage operation process. FRAM is used to describe the ship pilotage behavior, and then the results are combined with ACAT to analyze the factors leading to collision accidents and the coupling relationships between the factors for developing the structure of a DBN. To construct the DBN model, uncertainty methods such as the D-S evidence theory, a parameter adaptive learning algorithm (PALA) and a Markov model are used holistically to aid model parameters configuration. The research framework in Fig. 1 shows the three main research steps.

Step 1: Identifying RIFs and coupling relationships with FRAM-ACAT. On the basis of Hierarchical Task Analysis (HTA) for the functions (subtasks) identification of the ship's pilotage operation process, the FRAM is adopted to develop inter-level function model for describing system functions and identify potential variabilities and their critical coupling. Then, for each inter-level function, three intra-level functions are further identified to ensure the completion of the sub-task with ACAT model. Hence, the direct RIFs and their coupling relationships for the ship collision risk can be obtained from the inter-level functional resonance analysis and the intra-level functions resonance analysis can provide deep RIFs.

Step 2: Determining DBN model of risk evolution analysis. The topological structure of DBN is developed based on the identification results in step 1 to describe the complex relationship between the RIFs and collision accident evolution qualitatively. To parameterize the DBN model, the D-S evidence theory is used to fuse multiple experts knowledge to obtain nodes' prior probabilities. Then, the

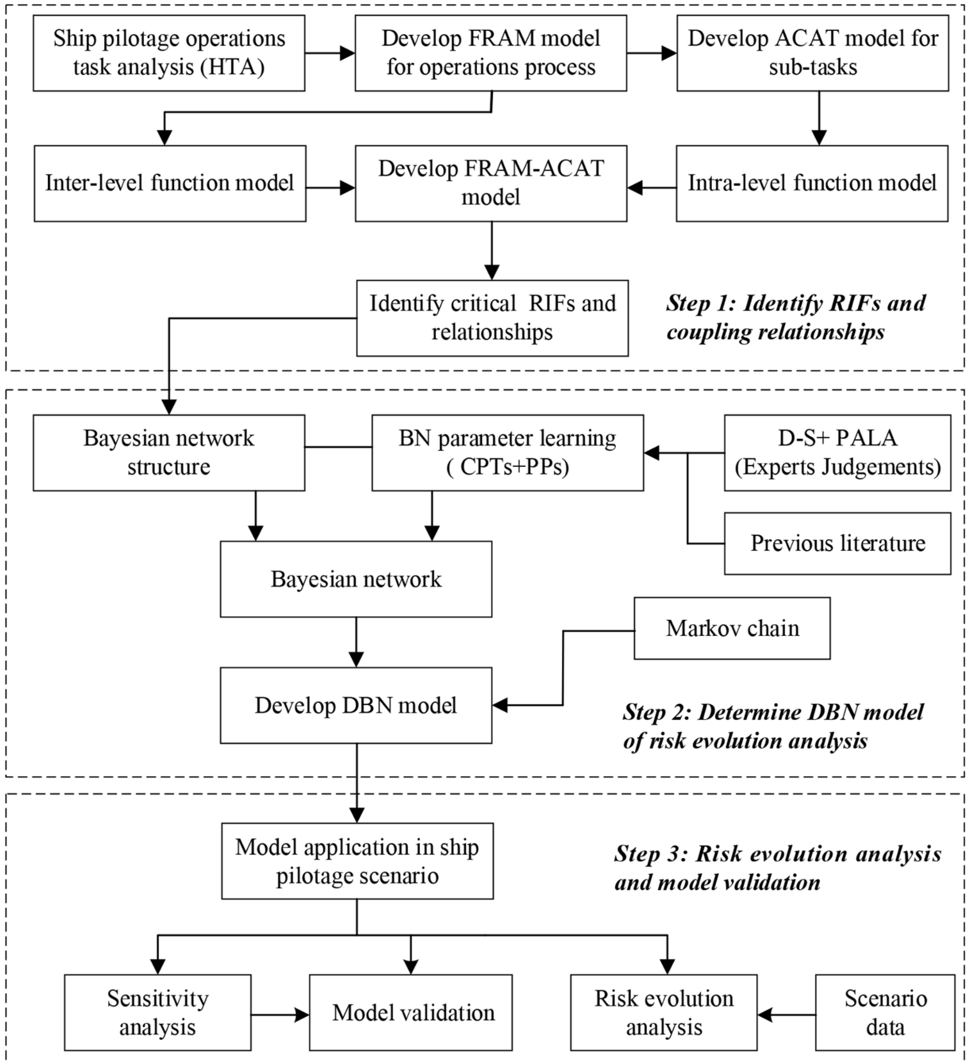

Fig. 1. Framework of risk evolution analysis in ship pilotage operations process.

PALA is used to calculate the CPTs between the parent node and its child nodes. Further, the Markov characteristics of the dynamic risk factors in the pilotage process are analysed to configure the TPTs based on probability distribution assumption and Markov model.

Step 3: Risk evolution analysis and model validation. The developed FRAM-DBN model is applied to the analysis of the collision risk evolution of a real ship pilotage operation process with scenario data. Not only the spatio-temporal evolution characteristics of the collision risk during the ship's pilotage operation, but also the critical RIFs can be obtained. Finally, the model is verified by various methods such as sensitivity analysis, literature comparison, expert validation, and face validity.

3.1. FRAM-ACAT modeling

The FRAM is integrated with ACAT to generate a proactive ship pilotage operational risk identification model, and provide an intuitive and structured way to characterize scenario-based RIFs and their relationships. For a detailed and rigorous description of functions, the ACAT model is used to enrich the FRAM by generating functions based on a closed-loop control system. Functional constraints and deep contributing factors to ship collision can be identified with the integrated model. As a result, the functional resonance analysis model can be developed and risk influencing factors and their coupling relationships for the pilotage operation failure leading to ship collision can be identified.

3.1.1. FRAM

In view of the dynamic and nonlinear coupling characteristics of the socio-technical system, FRAM reveals the mechanism of risk emergence through analysis of the system's normal operation [50]. The FRAM method is based on four basic principles: equivalence of failure and success, approximate adjustment, emergence, and functional resonance. Functions are categorized as human-, organization-, and technology-related functions, which are described from the six aspects of input (I), output (O), time (T), resource (R), precondition (P) and control (C). The variability of a function's output is determined in terms of time and precision, and the aggregation of its variability is estimated by examining the individual variability effects of a function, the variability effects of an upstream function on the downstream function, and the variability of the working conditions. The use of FRAM analysis in this paper is to identify the variability that leads to undesired outputs and to propose corresponding management strategies.

3.1.2. ACAT

Although ACAT was chiefly proposed for accident investigation and analysis, its essence is to construct a normal and continuous operational system mode based on the control loop. ACAT regards a complex system as a control system composed of four functional modules: actuator, sensor, controller, and communication. The safe and continuous operation of the system depends on the coordination and cooperation of the four types of functions. Therefore, ACAT provides a new risk analysis method based on the control loop, which is an analysis model that considers both structural decomposition and functional abstraction [54].

A closed-loop control mode proposed by ACAT is composed of four parts to coordinately complete the system function, and its logical relationship and meaning are shown in Fig. 2. Risks arise from failures or defects in system components and poor communication. Actuator generally refers to on-site operators who take actions according to orders; sensor refers to monitoring equipment or supervisors, whose task is to supervise the behavior of operators; controller is responsible for auditing and evaluating operation results according to standards; communication refers to the effective transfer of information between the above three types of functional modules.

3.1.3. FRAM-ACAT

The traditional FRAM method identifies functions by dividing a ship pilotage operations process into several sub-tasks, and then connects them according to their dependencies to describe the functional operation and coupling associations in a ship pilotage system. However, the process of function identification and description contains limitations of too much subjectivity and lack of unity and rigor. Using ACAT, each function in the FRAM model is regarded as a control loop, which is divided and functionally described from the actuator, sensor, controller, and communication perspectives. FRAM-ACAT [54] is a nested analysis method, with intra-level functions nested in each inter-level function. The inter-level function is constructed by the traditional FRAM method, while intra-level functions refer to the function modules in a closed-loop control structure using ACAT for each inter-level function. Due to the complex coupling relationship between various factors of the ship's pilotage operation system, the traditional risk analysis method is difficult to reveal factor coupling mechanism, this nested method can effectively identify the direct and deep-level RIFs and their coupling correlations regarding the risk of ship collisions in a ship pilotage process.

3.2. DBN modeling

As a dynamic probabilistic graphical model, DBN can be used to analyze temporal operational risk by using subjective and/or objective data. The FRAM-ACAT analysis results are used to construct the DBN topology structure, and then uncertainty methods such as D-S, PALA, and a Markov model are used to determine the model parameters' PP, CPT, and TPT according to the scenario of a ship's pilotage operations.

3.2.1. DBN

BN is the combination of probability theory, graph theory and decision theory. It is considered as one of the most effective theoretical models in the field of uncertain knowledge and probabilistic reasoning [42], which graphically represents the relationship between system variables. However, traditional BN ignores the correlation and complementarity of the information at the different time frames, which will cause either a loss of information or misjudgment of the actual state. Moreover, it is difficult to meet the inference requirements under complex dynamic environments and conditions with incomplete information.

DBN is an extension of BN under time series. It is a graphical representation of dynamic stochastic process under a stationary assumption, and, as such, can deal with dynamic risk reasoning problems under time series, it is very suitable. for the reasoning of temporal risks in the process of ship pilotage operations. DBN is represented as an even pair $\langle B_0, B_\rightarrow \rangle$, where B_0 is the initial BN that defines the probability distribution of $P(X)$ at the initial time, and $B_\rightarrow$ is a 2-TBN containing two time slices that define the conditional probability distribution between the variables of two adjacent time slices, the state transition probability is expressed as Eq. (1) .

$$P(X_t|X_{t-1}) = \prod_{i=1}^{n_t} P\left(X_t^i|Pa(X_t^i)\right) \tag{1}$$

Where, $P(X)$ is the set of variables; X_t^i is the ith node of the time slice t; $Pa(X_t^i)$ is the parent node of X_t^i; n_t is the number of nodes in the tth time slice.

In order to reduce the computational complexity of the model, the following two hypotheses are made [44].

(1) First-order Markov hypothesis: The edges between nodes in the DBN structure are either located in the same time slice or in adjacent time slices, and cannot span time slices;
(2) Stationarity hypothesis: The network topology and conditional probabilities do not change with time and remain unchanged during the study period.

According to the two hypotheses stated above, by expanding the DBN to the T time slices, a joint probability distribution across entire time slices is obtained, namely:

$$P(X_{1:T}) = \prod_{t=1}^{T}\prod_{i=1}^{n_t} P\left(X_t^i|Pa(X_t^i)\right) \tag{2}$$

Where, $X_{1:T} = \{X_1, X_2, \cdots, X_T\}$, represents the set of variables over T time slices.

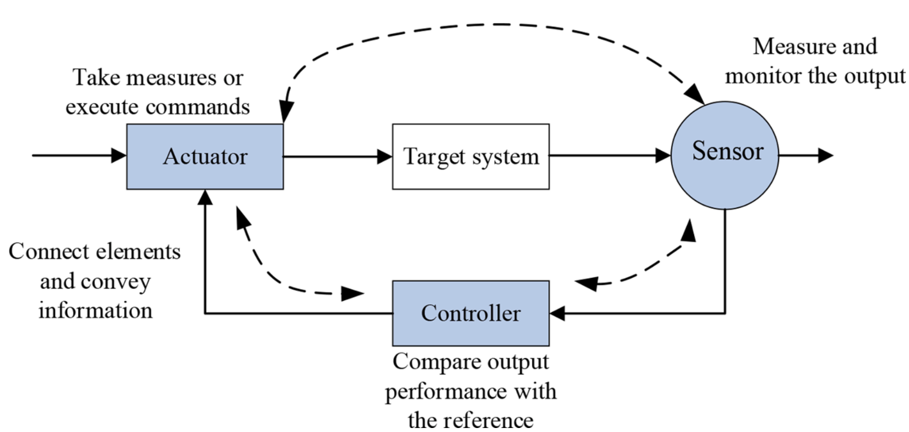

Fig. 2. A simplified closed-loop control diagram [54].

3.2.2. Establishment of conditional probability tables

The CPTs of BN nodes are used to represent the quantitative relationship between parent nodes and child nodes within the same time slice, and are generally obtained through the accident data learning, logical analysis, as well as expert judgment. In this paper, the conditional probabilities of parent-child nodes with logical gate relationships are obtained through logical analysis. Due to the differences in the correlation among factors in different ships pilotage scenarios, it is difficult to obtain CPTs through data learning due to the lack of targeted data for specific scenarios. As a scenario-based CPT calculation method, the PALA is used to obtain the CPTs of the child nodes under the comprehensive influence of the parent nodes [63]. The steps are as follows:

(1) According to the dependencies between nodes in the BN model, assuming that the state of a parent node X is $X_i(i = 1, 2, \cdots, n)$, one state of its child node Y is $Y_j(j = 1, 2, \cdots, m)$. Obtaining the CPT is to calculate the $p(Y_j|X_i)$. For this parent node X_i, the states of its child nodes are sorted in an ascending order.
(2) For a parent node, the related child nodes corresponding to its different states are different. Therefore, it is necessary to find out the related child nodes and irrelevant child nodes corresponding to each state of the parent node.
(3) Find out the most preferred and least preferred relationship between a state of the parent node X_i and the states of its related child nodes $Y_j(j = 1, 2, \cdots, m)$, and form an ascending order of CPT, for instance, the order of CPT for a certain child node Y of the parent node state X_i represents as $p(Y_1|X_i) < p(Y_2|X_i) < \cdots < p(Y_m|X_i)$.
(4) According to the importance of the child node, a negative high-power function is used to form the conditional probability [63], as shown in Eqs. (3) and (4).

$$P(Y_j|X_i) = 1 \Big/ j^k \sum_{j=1}^{m} \frac{1}{j^k} \tag{3}$$

$$\sum_{j=1}^{m} P(Y_j|X_i) = 1 \tag{4}$$

where, $P(Y_j|X_i)$ is the conditional probability when X is in state X_i while Y is in state Y_j, and k is a negative high-power coefficient, which is determined by experts according to the ship pilotage scenario.
(5) Find out the most preferred and least preferred relationship between the parent node state and the states of irrelated child nodes to form an ascending CPT order;
(6) According to the importance of the child nodes, the method of negative high-power function is used again to form the conditional probability. So far, the CPTs between all parent nodes and child nodes may be obtained.

3.2.3. Establishment of transition probability

TPTs represent the probability distribution of the state transition of dynamic nodes in DBN over time, for variable nodes with Markov characteristics, the TPT is generally obtained by combining probability distribution assumptions and the Markov model [64]. The process of ship pilotage is a process in which the ship's man-machine system continuously adapts to the complex and changeable environment and safely completes tasks such as navigation, berthing/berthing et al., so the RIFs in the ship pilotage operations process mainly include three categories: human factors, technical factors and environmental factors. Since the conditional probability distribution of the future state of the ship's man-machine system in the stochastic process of pilotage operations only depends on the current state, the state transition of human and technical factors presents Markov characteristics in the ship pilotage operations process, thereby their TPTs may be calculated using Markov model. The state of environmental factors presents a random mutation characteristic with the transition of the ship's position during the pilotage process, which does not satisfy the Markov characteristic. Therefore, the nature of the environmental nodes is set to be deterministic in the DBN, and the temporal states of environmental nodes are obtained through observation data based on instruments.

According to the Markov hypothesis, the state transition matrix of the technical factors is shown in Eq. (5). The states of the technical factors of the investigated ship are divided into three types: normal (N), partial failure (PF) and failure (F). According to the statistical law, the failure probability of ship equipment is in alignment with a negative exponential distribution (Chang et al. [65]). Due to the time limit of the ship's pilotage operations process, the equipment's maintenance rate is not considered when determining the state transition probability, so only the failure rate of equipment is considered: λ_1 (N to F), λ_2 (N to PF), λ_3 (PF to F). The TPTs of the technical factors are obtained according to a negative exponential distribution function as shown in Eq. (6).

$$Ti = \begin{bmatrix} 1-(\lambda_1+\lambda_2)\Delta t & \lambda_2\Delta t & \lambda_1\Delta t \\ 0 & 1-\lambda_3\Delta t & \lambda_3\Delta t \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

$$P_T = \begin{bmatrix} e^{-(\lambda_1+\lambda_2)\Delta t} & \frac{\lambda_2}{\lambda_1+\lambda_2}\left(1-e^{-(\lambda_1+\lambda_2)\Delta t}\right) & \frac{\lambda_1}{\lambda_1+\lambda_2}\left(1-e^{-(\lambda_1+\lambda_2)\Delta t}\right) \\ 0 & e^{-\lambda_3\Delta t} & 1-e^{-\lambda_3\Delta t} \\ 0 & 0 & 1 \end{bmatrix} \tag{6}$$

Human error in a ship pilotage operations process is a random event. According to statistical laws, it is reasonable to assume that it adheres to a Poisson distribution, whereby the states of the human errors are divided into Yes (Y) and No (N). Let that the number of human errors occur per unit of time is λ, the probability of human errors occurring n times per unit of time is calculated by Eq. (7). The state transition of human error satisfies the Markov characteristic [64], so the TPT of human error is shown in Eq. (8).

$$P\{N(t+\Delta t) - N(t) = n\} = e^{-\lambda t}\frac{(\lambda t)^n}{n!} \tag{7}$$

$$P_T = \begin{bmatrix} 1-e^{-\lambda_4\Delta t} & e^{-\lambda_4\Delta t} \\ \lambda e^{-\lambda_4\Delta t} & 1-\lambda e^{-\lambda_4\Delta t} \end{bmatrix} \tag{8}$$

3.2.4. Establishment of prior probability

The PP reflects the state probability distribution of an uncertain node at the initial time slice, and the acquisition method is different due to the type of a variable. Environmental factors such as wind, current, visibility and traffic density during a ship pilotage operation process can be observed or received using instruments, so their states are deterministic in a specified time slice. The states of human and technical factors have random uncertainty, and it is difficult to obtain their PP distribution through direct observation. It is therefore necessary to use subjective data from expert judgement to compensate the incompleteness/unavailability of the objective data in this setting. The PP of human factors is evaluated by experts based on the historical performance of pilots, and the one of technical factors is evaluated by experts based on data such as ship PSC records, ship age, and maintenance records. In order to improve the accuracy of expert evaluation, this paper uses the failure probability of the corresponding factor in the relevant ship collision risk research literature as the benchmark, and sets a failure probability interval based on the benchmark for experts to evaluate. In the end, the D-S evidence theory is used to fuse the evaluation results of different experts to obtain the final prior probability [43].

3.3. Risk evolution of ship pilotage operation process

3.3.1. Ship pilotage process risk

A ship pilotage process refers to the operation process of completing all the tasks of ship navigation, berthing, unberthing and shifting when a ship enters/leaves a port, with the assistance of a qualified pilot. The safe implementation of pilotage tasks depends on the cooperation of the pilot and crews, reliable operation of ship equipment, good communication and coordination with stakeholders, effective acquisition of environmental information, accurate judgment and response to hazards [3]. Fig. 3 describes the entire pilotage process of a ship entering and berthing from t_0 to t_n, the scope of this paper is to investigate the evolution characteristic of ship collision risk during the ship navigation from the pilot boarding at time t_1 to the quayside at time t_j.

Each subtask may be regarded as a functional module, and the realization of its function is completed by its internal actuators, sensors and controllers, and the coupling effect between functions is a universal aspect throughout the entire process of ship pilotage. Ship pilotage process risk emerges when the functions cannot achieve normal output due to the change of the components' state in functional modules during pilotage operation. The resonance effect is generated through the coupling relationship between the functions, so that a change in the risk of the pilotage process emerges. Assuming that the risk performance of a ship, at any time t in the pilotage process is $R^t \in [0,1]$, where 0 means absolute safety, and 1 means the occurrence of a ship collision. It is expressed by Eqs. (9) and (10).

$$R^t = R^t_{Hi} \otimes R^t_{Tj} \otimes R^t_{Ok} \tag{9}$$

where, R^t_{Hi} represents the output risk performance of the ith human functional module at time t, the functional output changes of operators due to factors such as physiological, psychological, or external influences; R^t_{Tj} represents the output risk performance of the jth technical functional module at time t, the functional output changes of ship equipment due to the factors such as maintenance, repairment, or the external environment; and R^t_{Ok} represents the output risk performance of the kth organizational function module at time t, the functional output changes of the bridge team due to factors such as communication, teamwork, and supervision; $\otimes$ is the coupling algorithm, which represents the measurement of the nonlinear relationship between variables.

$$\begin{cases} R^t_m = f\left(A^t_m\right) \otimes f\left(S^t_m\right) \otimes f\left(C^t_m\right) \\ A^t_m = A^{t-1}_m \bullet T_1 \\ S^t_m = S^{t-1}_m \bullet T_2 \\ C^t_m = C^{t-1}_m \bullet T_3 \end{cases} \tag{10}$$

where, R^t_m represents the output risk performance of the mth functional module at time t; $f(A^t_m)$, $f(S^t_m)$, $f(C^t_m)$ which represent the risk performance functions of the actuator, sensor, and controller of the mth functional module at time t, respectively; T_1, T_2, T_3 which are the state transition matrix of the behavioral state of the mth functional module's actuator, sensor and controller from $t-1$ to t.

3.3.2. Risk evolution in a ship pilotage operation process

The risk evolution in a ship pilotage operations process in this paper refers to the spatiotemporal distribution of the collision risk performance that emerges from upstream and downstream coupling associations due to the continuous behavior vulnerabilities of each functional module. Ship pilotage operations include a series of sub-tasks collectively handled by a bridge team involving a pilot, such as environmental perception, hazard judgment, action decision-making, and execution of collision avoidance action. Each functional module performs sub-tasks with temporal changes in the environment during the pilotage process. The collision risk is not a simple linear causal secondary consequence, it is difficult to judge the performance of the risk through the identification and causal reasoning of human error or equipment failure. The FRAM method, based on the perspective of Safety II [52], may reveal the risk emergence mechanism in the ship pilotage process. When being integrated with the dynamic quantification of DBN, it can reveal the risk evolution law of a pilotage process.

4. Case study

A case study of a container ship, via the Beicao deep-water channel from its pilot boarding place to quayside is used to demonstrate the feasibility of the proposed model towards the estimation of the risk temporal probability of ship collision during the navigation process. The chosen trip is representative as the ship type and size are the most common ones in the pilotage practice in Shanghai port, one of the busiest ports in the world.

4.1. Scenario description

In this section, a real case analysis is conducted by the investigation of the spatiotemporal evolution of the collision risk in the pilotage operations process of a container ship sailing from the Yangtze River estuary to Shanghai Waigaoqiao Pier No. 2 via a deep-water channel of the Yangtze River. In this case, the pilot boarded the ship from buoy D6 at 15:23 pm on March 23, 2022 (4 h before the high tide of Zhongjun). The navigation phase of ship pilotage process from buoy D6 to D47 is 42 nautical miles and lasts 4 h and 30 min, with the ship pilotage scenario parameters are obtained from the relevant objective database and shown in Table 1.

The main tasks in the ship pilotage operations process are to locate the ship properly and avoid collisions. The pilot should judge the collision risk of the ship at any time, control the navigation elements

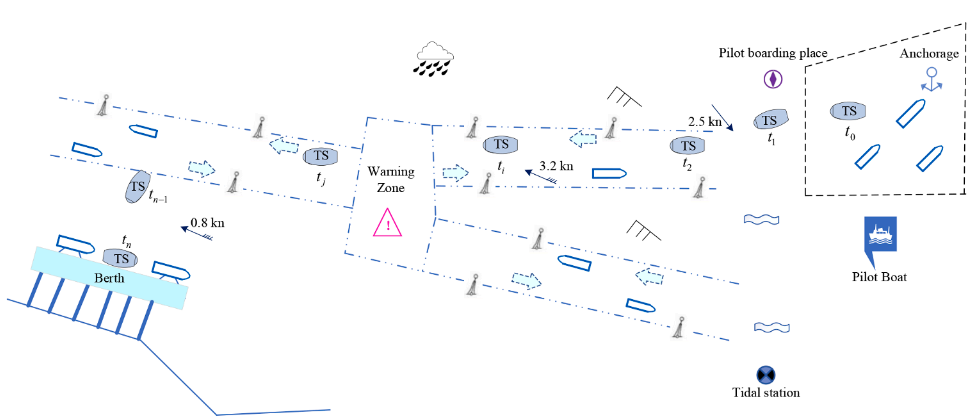

Fig. 3. Schematic diagram of the ship pilotage process.

Table 1
Ship pilotage scenario parameters.

Parameter	Description	Parameter	Description	Parameter	Description
Length	249 m	Visibility	Good	Wave height	0.3 m
Width	37 m	Initial Position	D6 buoy	Wind	6.8 m/s
Draft	9.6 m	Final position	D47 buoy	PSC defect	No
Cargo	7600TEU	Ship age	10 years	Pilot level	A2
Registry	Panama	Voyage time	4 h 30min	Average speed	10 kn

such as the ship's course, speed, and position after analyzing the hydrometeorological and traffic environments around the ship. According to the analysis of the risk characteristics of the pilotage scenario, the FRAM-ACAT method is used to analyze and identify the RIFs and their coupling correlations in the ship pilotage operations process.

4.2. Risk identification in the ship pilotage operations process

After the scenario analysis of the ship pilotage process [2], HTA is implemented to identify and describe the functions (missions) in the pilotage operations process (as shown in Fig. 4). Aiming at the target of navigation safety and collision avoidance in the ship pilotage process, the pilotage operation process is divided into several subtasks, such as "Identify danger of collision", "Take collision avoidance actions", "Adjust ship's position", "Keep a safe distance", and "Ensure navigation safety". By further dividing these subtasks, some specific subtasks at the operational level are obtained.

The function identification is carried out according to the results of the HTA analysis in Fig. 4, thereby the 7 key operational tasks of implementing ship collision avoidance to ensure ship safety are taken as functional modules, i.e. "Maintain a proper look-out", "Judge the collision risk", "Take action to avoid collision", "Adjust the proper course", "Adjust the proper speed", "Keep a safe distance from other ships", and "Maintain normal operation of equipment". On this basis, the FRAM method is used for functional description and coupling correlation analysis. First, combined with the specific pilotage operation scenario analysis, each functional module is described and analyzed from six aspects of I, O, T, R, P, and C. Then, by identifying whether the output of the upstream function is the I, T, R, P or C of downstream functions, that is, the coupling relationship between the upstream and downstream functions, the FRAM model for the functional resonance analysis of the ship's pilotage operation is established (as shown in Fig. 5).

For example, the outputs of the "Maintain normal operation of equipment" function are "Radar in order", "Main engine in order" and "Rudder equipment in order". "Radar in order" is the R of the function "Maintain a proper look-out", "Main engine in order" is the P of "Adjust the proper speed", and "Rudder equipment in order" is the P of "Adjust the proper course", so "Maintain normal operation of equipment" as the upstream function realizes the coupling action with its downstream functions through the association between its output and the different characteristics of the three downstream functions. It is noteworthy that, due to the complex and changeable environment of ship pilotage operations, ship characteristics, and the human factors, the functions description and coupling relationship between functions are not fixed, but depend on the actual pilotage operation scenarios.

On the basis of function identification and description, the variability of each function output in the FRAM model is analyzed from the aspects of time and precision, thereby further revealing how individual functional variability can be associated with functional resonance through functional coupling actions (i.e. the generation mechanism of undesired outputs). Then, the ACAT method is used to describe and analyze the internal operating mechanism of each function from the three aspects of actuator, sensor, and controller. Identifying and analyzing for intra-level functions are implemented by explaining the internal mechanisms and causes of unfavorable outputs for each function. Refer to ship operation risk analysis in Uddin and Awal [66], the description, output and variability of inter-level and intra-level functions in the ship pilotage process are shown in Table 2.

Thus, according to the FRAM-ACAT analysis in Table 2, normal operational functions and internal control sub-functions required for safe navigation during the ship pilotage process are identified. According to the principle of equivalence of success and failure, the abnormal variability of functional output will generate functional resonance through the coupling of upstream and downstream functions, thus resulting in the emergence of risk. The inter-level functional resonance analysis can obtain the direct RIFs of ship collision risk, and the intra-level functional resonance analysis can obtain even more specific and in-depth RIFs. Combined with the scenario analysis of the ship pilotage process, the influencing factors of the functions were further analysed by referring to related studies, the identification results of collision RIFs are shown in the Table 3. For example, for the look-out function, its failure output "Inadequate look-out" constitutes a direct RIF that affects the ship collision, and "Inadequate human look-out" and "Radar failure" as internal causes of "Inadequate look-out" constitute the deep RIFs of ship collision.

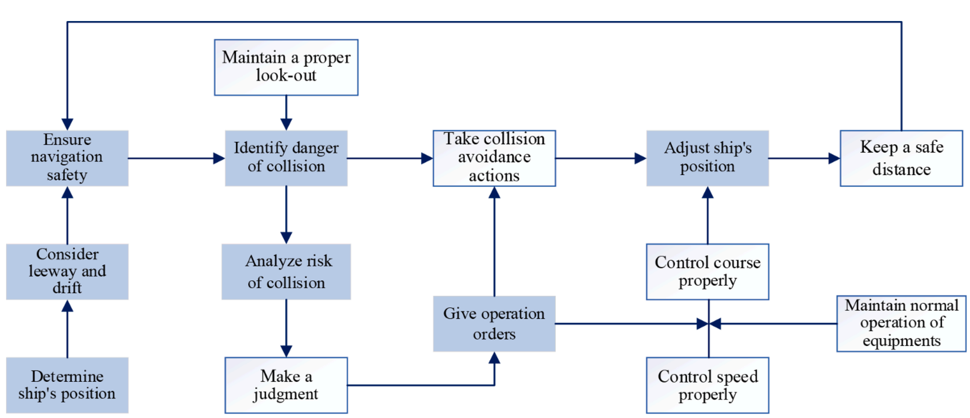

Fig. 4. HTA analysis in ship pilotage process.

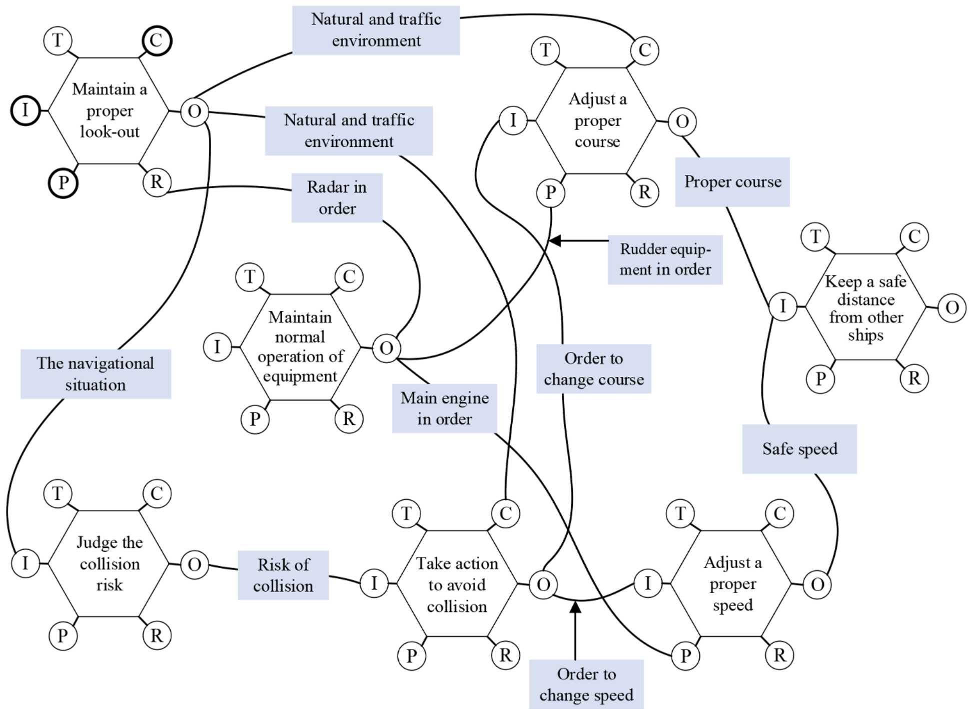

Fig. 5. Functional resonance analysis in ship pilotage process based on FRAM.

4.3. DBN modeling

According to the risk identification results of the ship pilotage process, the DBN topological structure (Fig. 6) is developed by the pilotage risk evolution analysis as follows. The direct RIFs and deep-level RIFs in Table 3 are converted into nodes, and the coupling relationships between RIFs are converted into directed edges in the DBN. Among them, 11 nodes are set as dynamic nodes, including "Pilot in poor condition", "Unfamiliar with handling performance", "Inadequate supervision by captain", "Inadequate supervision by pilot", "Inadequate human look-out", "Miscoordination with others", "Main engine failure", "Rudder equipment failure", "Radar failure", "Leeway and drift angle", "Ship navigation density", while other nodes are static. Among the dynamic nodes, "Leeway and drift angle" and "Ship navigation density" are set as deterministic node, their temporal states are obtained from observations. The other dynamic nodes are chance nodes, and their probability distributions are jointly determined by their prior and transition probabilities. The states of "Main engine failure", "Rudder equipment failure" and "Radar failure" are defined as Normal (N), Partial failure (PF) and Failure (F); the states of "Leeway and drift angle" and "Ship navigation density" are classified as Large, Medium and Small; and the states of the remaining nodes are Yes (Y), and No (N).

The calculation of leeway and drift angle γ is undertaken by Eq. (11).

$$\gamma = TD - TC \tag{11}$$

where, *TD* represents the track direction of the ship, *TC* represents the true course of the ship.

According to the wind and current statistics in the research waters and the experts' practical experience, the angle is defined by the three states of Large ($\gamma \geq 10°$), Medium ($5° \leq \gamma < 10°$), and Small ($\gamma < 5°$). During the ship pilotage process, the data of track direction and true course of the ship are obtained from its AIS and RADAR data.

A ship domain is usually defined as an area around the ship that its navigators want to maintain clear from other ships, and it is often used for situational assessment and monitoring of the collision risk with other ships [69]. The number of other ships in the ship domain during the ship pilotage process reflects the degree of the surrounding navigational complication, which may be used to characterize the ship navigation density around the own ship [70]. The relevant ship parameters in this pilotage operation process are shown in Table 1. According to the test results of Pietrzykowski et al. [71], the ship domain for judging the navigation density of ships is set to be an ellipse, with the ship's center offset out of the ellipse axis (Fig. 7). The long semi-axis of the domain in the heading direction is set to 4.5L(L is length of the ship), and its short semi-axis is set to 2 L. The number of other ships in the ship domain is δ, and the ship navigation density is divided into Large ($\delta \geq 3$), Medium ($\delta = 2$), and Small ($\delta \leq 1$). The temporal number of ships in the ship domain during the ship pilotage process is obtained through AIS dataset and RADAR observation records.

4.4. Quantification of DBN parameters

The parameters of the established DBN model are defined in three categories: PP, CPT and TPT of dynamic nodes. With respect to the BN-based maritime risk papers using expert judgements [23,25], five experts (detailed in Table 4) are selected and invited to assess the PP of the nodes in the DBN model.

By analyzing the characteristics of each node in the DBN topology, a total of 11 nodes need to obtain a PP or initial state. Among them, the two environmental factors X_7 and X_8 are deterministic nodes, and their initial states can be obtained through the actual observation of instruments. X_1, X_3, X_4, X_5, and X_6 are the nodes of human operational error factors. Referring to the operational error probability related to ship collision avoidance in the Shanghai port waters in [19] (as the benchmark of Cognitive Failure Probability (CFP_0)), a new interval is set by having $\pm 10\%$ CFP_0 as the lower and upper bounds, respectively. The five experts estimated the failure probability of the five factors within the given probability interval according to the scenario parameters of the ship's pilotage operation and the historical performance of the pilot. Finally, the D-S evidence theory was used to fuse the estimated results of the five experts and the values obtained as the PP of the network nodes are shown in Table 5.

The prior probability of X_2, X_9, X_{10}, X_{11} in DBN is the failure probability of pilot's physical condition and ship's technical status, the

Table 2
Representation and variability of outputs for ship pilotage process.

Inter-level function	Intra-level function	Output	Variability of output
Maintain a proper look-out	Maintain visual lookout and radar lookout; Pilot and captain supervision; Relevant rules and pilotage expertise	The navigational situation; Natural and traffic environment	Not at all, imprecise, or too late
Judge the collision risk	Pilot judges the collision risk; Captain supervision; Collision avoidance rules and pilot expertise	Risk of collision	Not at all, imprecise, or too late
Adjust a proper speed	Third officer undertakes the main engine operation; Pilot supervision, instrument monitoring; Recite orders and standardize operations	Safe speed	Not at all, imprecise, or too late
Adjust the course	Helmsman steering; Pilot supervision, instrument monitoring; Recite orders and standardize operations	Proper course	Not at all, imprecise, or too late
Take action to avoid collision	Pilot gives operation orders; Captain supervision; Regulations and hazard judgments	Order to change speed; Order to change course	Not at all, imprecise, or too late
Maintain normal operation of equipment	Ship equipment functions normally; Instrument, pilot and crews monitoring; Regular maintenance and inspection before sailing	Equipment in order	Not at all, imprecise, or too late
Keep a safe distance from other ships	Pilot and crew operation; Pilot, captain supervision, instrument monitoring; Regulations and pilot expertise	Acceptable collision risk	Not at all, imprecise, or too late

Table 3
Identification of ship collision RIFs.

NO	Functional failureDirect RIFs	Intra-functional failureDeep RIFs	Refs.
1	Inadequate look-out (X_{12})	Inadequate human look-out(X_1); Radar failure(X_{11})	[19]
2	Pilot misjudgment (X_{16})	Pilot in poor condition(X_2); Inadequate look-out(X_{12}); Miscommunication with others(X_5)	[3]
3	Improper speed control(X_{17})	Improper operation orders(X_{13}); Improper operation of main engine(X_{14}); Main engine failure(X_9); Inadequate supervision by pilot(X_6)	[66]
4	Improper course control(X_{18})	Improper operation orders(X_{13}); Helmsman operation error(X_{15}); Rudder equipment failure(X_{10}); Large leeway and drift angle(X_7); Inadequate supervision by pilot(X_6)	[66]
5	Improper operation orders (X_{13})	Pilot misjudgment(X_{16}); Unfamiliar with handling performance(X_3); Inadequate supervision by captain(X_4)	[67]
6	Unreasonable output of ship equipment	Equipment failure (X_9, X_{10}); Improper operation of equipment (X_{14}, X_{15}); Inadequate supervision (X_4, X_6)	[68]
7	Existence of collision risk(X_{22})	Improper position control (X_{19}); Improper emergency action (X_{20}); Large navigation density(X_8); Forming close quarters situation(X_{21})	[32]

expert judgment method was used to obtain the failure probability due to the lack of relevant targeted accident data. In order to improve the accuracy of expert evaluation, this paper referred to the failure probability of related factors in Ugurlu and Cicek [72] (as the benchmark of prior probability (PP_0)). A new interval is set by having $\pm 10\% PP_0$ as the lower and upper bounds, respectively. The five experts estimated the failure probabilities of the five factors within the given evaluation interval according to the scenario parameters of the ship's pilotage operation, the ship's PSC inspection records and the pilot's historical performance. Finally, the D-S evidence theory was used to fuse the estimated results of the five experts and the values obtained as the PP of the network nodes are shown in Table 6.

By using a logical analysis and PALA, the CPTs between each child node and their parent nodes are obtained. In the PALA method, five experts configured the values of the negative high-power coefficient K for different parent-child nodes according to the ship's pilotage operation scenario. Then, after taking the average, Eqs. (3) and (4) were used to obtain the CPTs between the parent and child nodes. Referring to Fowler and Sorgard [73], the failure/error probabilities of partial dynamic nodes are shown in Table 7, which are respectively input into Eqs. (5)–(8) to obtain the TPTs of dynamic nodes. After the values of all network parameters are input into the DBN model for inference, the temporal distribution of collision risk in the ship pilotage process is obtained. It is noteworthy that in this probability configuration process, the used AIS data is used and purified. The AIS allows the automatic exchange of navigational information between ships and shore stations, which has become an important data source to describe ship traffic flow characteristics that have been used in maritime risk assessments [23]. However, AIS data have some widely known flaws and typical errors with relevant data trustworthiness and reliability, which are usually related to human errors, software, or hardware deficiencies and are considered inevitable [24]. In this paper, AIS records dataset corresponding to ships trajectories in the deep waterway of the Yangtze River between 15:23–19:53 pm on March 23, 2022 in the studied area is obtained from the Wusong VTS control center. The numbers of other ships in the ship domain during each time slice during ship navigation process are extracted from the AIS dataset, so as to determine the states of the ship navigation density in each time slice. In order to avoid the calculation errors caused by the flaws of the AIS data or the lack of AIS on some small ships, the number of ships in the ship domain in each time slices is comprehensively determined by combining the shipborne RADAR data records. In addition, for the calculation of the leeway and drift angle, the heading and track direction of the ship in each time slice are comprehensively determined according to the AIS and RADAR data records. Then, the leeway and drift angle can be obtained according to Eq. (11), so as to determine the state of leeway and drift angle in different time slices.

4.5. Risk evolution analysis in the ship pilotage operations process

The ship pilotage process lasted 4 h and 30 min, since sailing time of the ship between two buoys was about 6 min, allocating every 6 min as a time slice, whereby the entire process was divided into 45 time slices. The relevant TPT were input into DBN for inference, whereby the temporal distribution of ship collision risk is obtained as shown in Fig. 8. The results show that the collision risk in the initial and the final stage of the ship pilotage process is relatively high, while at the middle stage they are relatively stable, and at a low risk level, indicating that the overall process risk evolution presents a U-shaped curve. From t0 to t44, the probability distribution of ship collision risk is 4.84E-05~7.37E-03, and the change rate of collision probabilities during the entire pilotage process is 15,127%, with a very large fluctuation range. It indicates that the dynamic coupling effect of various RIFs in the ship pilotage process has a significant impact on collision risk. Plotting the temporal state data of "Ship navigation density" and "Leeway and drift angle" to the evolution curve of ship collision risk (Fig. 8), it discloses that their temporal

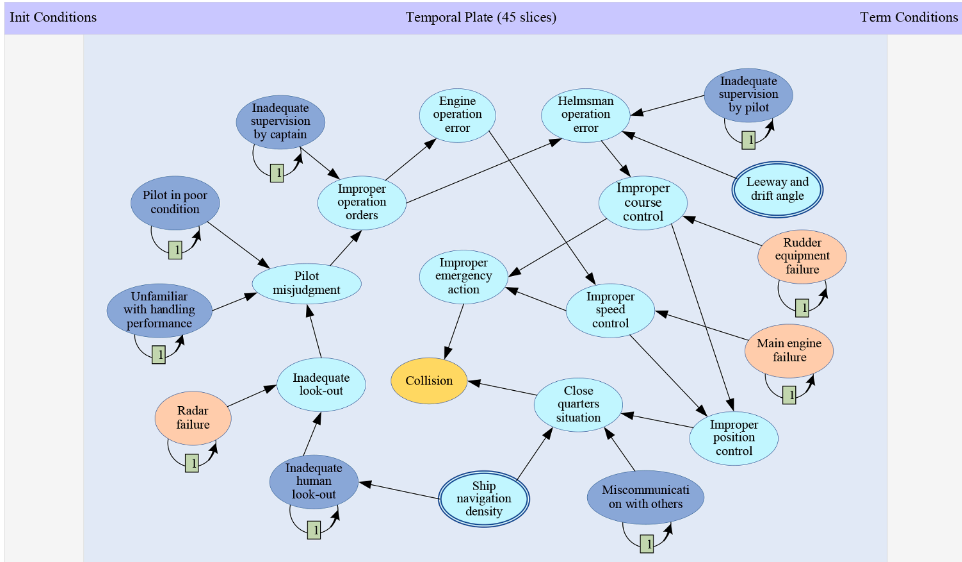

Fig. 6. DBN model for risk evolution analysis in ship pilotage process.

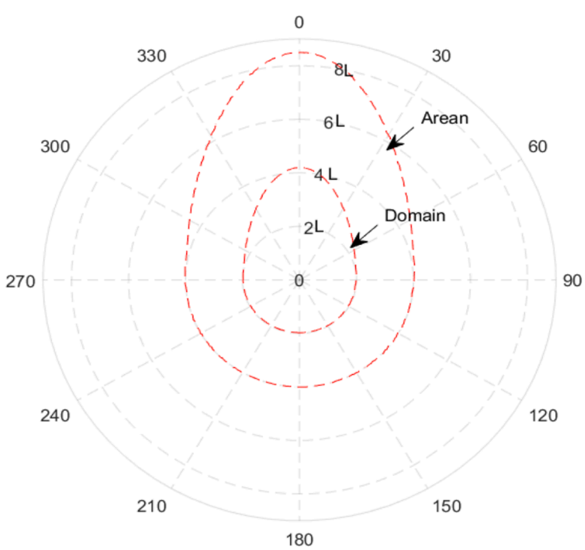

Fig. 7. Ship domain for judging navigation density.

state distributions are congruent with the overall trend of collision risk, indicating that two RIFs have significant influence on the ship collision risk during the pilotage process. When comparing the two factors, the influence of "Ship navigation density" is more significant. Particularly in time slices of *t2, t37*, and *t42*, the superimposed effects of the two RIFs cause a sharp increase in collision risk, which means that the coupling of the two factors with other RIFs produces a resonance effect during the pilotage process, resulting in a surge in the ship pilotage system risk.

4.6. Sensitivity analysis

Sensitivity analysis is mainly used to investigate how the state changes of some variables influence on the target object, in order to quantify the importance of system variables [64]. As a special relative entropy, mutual information is used to measure the degree of association between random variables. The larger the value, the greater degree of association between the variables is. Sensitivity analysis is often used to identify the RIFs [74], which are particularly sensitive to ship collision. The mutual information between variables *X* and *Y* may be calculated by

Table 4
Details of the panel of experts.

Expert NO.	Institution	Education	Age	Experience	Gender
Expert 1	Maritime Safety Administration	Master degree	34	He has worked as an officer in Wusong VTS of Shanghai MSA for 8 years, has extensive experience in identifying ship hazard scenarios	Male
Expert 2	Pilot station	Bachelor degree	47	As a senior pilot of the Shanghai Pilot Station, he has years of experience piloting large container ships in the waters	Male
Expert 3	Shipping company	Bachelor degree	51	As a captain of container ships, he has years of experience navigating ship in Shanghai port waters	Male
Expert 4	Pilot station	Bachelor degree	45	As an officer of the Shanghai Pilot Station, he is responsible for assisting in the formulation and review of pilot schemes for ships in the waters	Male
Expert 5	University	Doctor Degree	48	He was a chief officer in ocean-going ships and has been engaged in ship safety management research for 15 years in a world leading maritime university	Male

Table 5
Prior probability of the human operational RIFs.

Operational errors	Cognitive function	Generic failure type	Reference value	Refs.	Scenario value based on D-S
X_1	Observation	Inadequate observation	3.79 E-02	[19]	4.2E-02
X_3	Interpretation	Delayed interpretation	5.42 E-03	[19]	4.7E-03
X_4	Interpretation	Faulty diagnosis	5.42 E-03	[19]	7.6E-03
X_5	Execution	Missed action	1.63 E-02	[19]	5.3E-03
X_6	Interpretation	Faulty diagnosis	5.42 E-03	[19]	3.6E-03

Table 6
Prior probability of physical and technical failure RIFs.

Basic events	States	Reference failure probability	Refs.	Failure probabilitybased on D-S
X_2	Y	1.63E-03	[72]	2.6E-03
X_9	PF	5.57E-04	[72]	1.2E-04
	F	5.57E-04		5.8E-04
X_{10}	PF	1.86E-04	[72]	3.5E-04
	F	1.86E-04		8.3E-04
X_{11}	PF	4.18E-04	[72]	2.2E-04
	F	4.18E-04		4.6E-04

Table 7
Failure rate and error rate of RIFs.

RIFs	States	Failure/ Error rate
Radar failure	PF	3.20E-05
	F	1.60E-05
Main engine failure	PF	4.80E-05
	F	1.10E-05
Rudder equipment failure	PF	6.30E-05
	F	4.70E-05
Unfamiliar with handling performance	Y	3.40E-04
Pilot in poor condition	Y	1.80E-04
Inadequate supervision by captain	Y	3.20E-04
Inadequate supervision by pilot	Y	2.80E-04
Miscommunication with others	Y	6.30E-04
Inadequate human look-out	Y	8.50E-04

the Eq. (12).

$$H(X:Y) = \sum_{y\in Y}\sum_{x\in X} p(x,y)\log_2\left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{12}$$

where, $p(x,y)$ is the joint probability distribution function of X and Y; $p(x)$ and $p(y)$ are the marginal probability distribution functions of X and Y.

$X_1, X_2, X_3, X_4, X_5, X_6, X_9, X_{10}, X_{11}$ were selected as the research objects, the state of "Collision" node was set to "Y" in time slices *t0, t15, t30*, and *t45* for backward analysis, and the posterior probabilities of the nine RIFs were obtained, then the mutual information values of RIFs at 4 time slices were calculated according to Eq. (12), with the results shown in Fig. 9. The influential degree of each RIF shows an increasing trend with time, and the most prominent factors are X_1 (Inadequate human look-out), X_5 (Miscommunication with others), X_2 (Pilot in poor condition), X_3 (Unfamiliar with handling performance), X_6 (Inadequate supervision by pilot), whereby the impact of each RIF on the collision risk at different time slices is $X_1 > X_5 > X_2 > X_3 > X_6$. The strength influence analysis was carried out in the BN modeling software GeNIe, and the results shown in Fig. 10 are consistent with the calculation results of the mutual information value, further verifying the validity and sensitivity of the model. The results show that maintaining a proper look-out is essential to detect the danger of collision in time and avoid the occurrence of collision. The ship pilotage waters are limited by the depth of water and the width of the channel, so the maneuverability space is limited, and due to the large navigation density and a high number of surrounding ships, it is necessary to maintain effective communication and coordination with other ships to avoid collision.

The RIFs of "Ship navigation density" and "Leeway and drift angle"

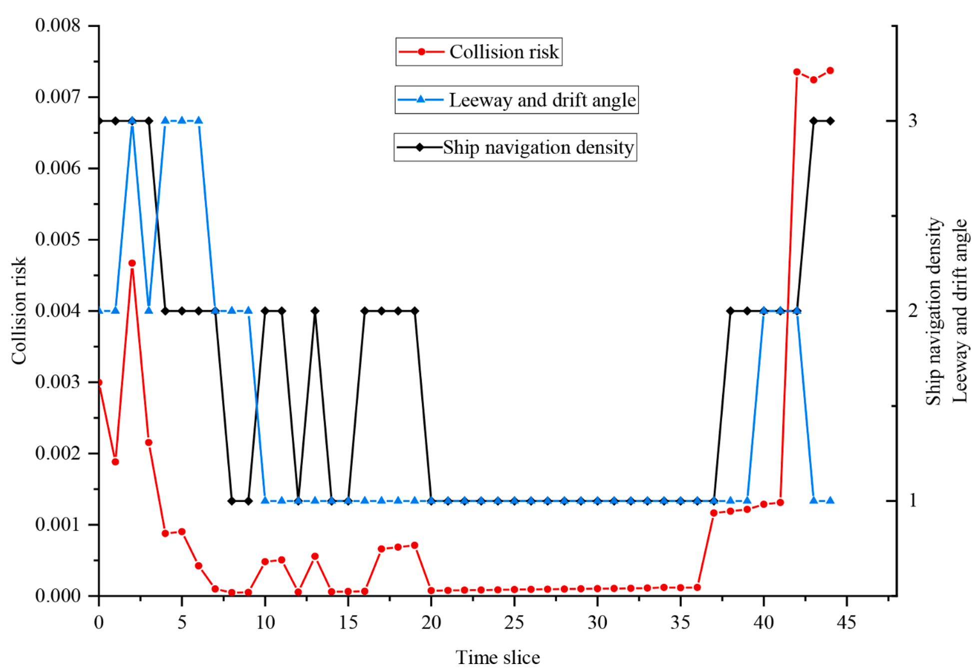

Fig. 8. Risk evolution curve in ship pilotage process.

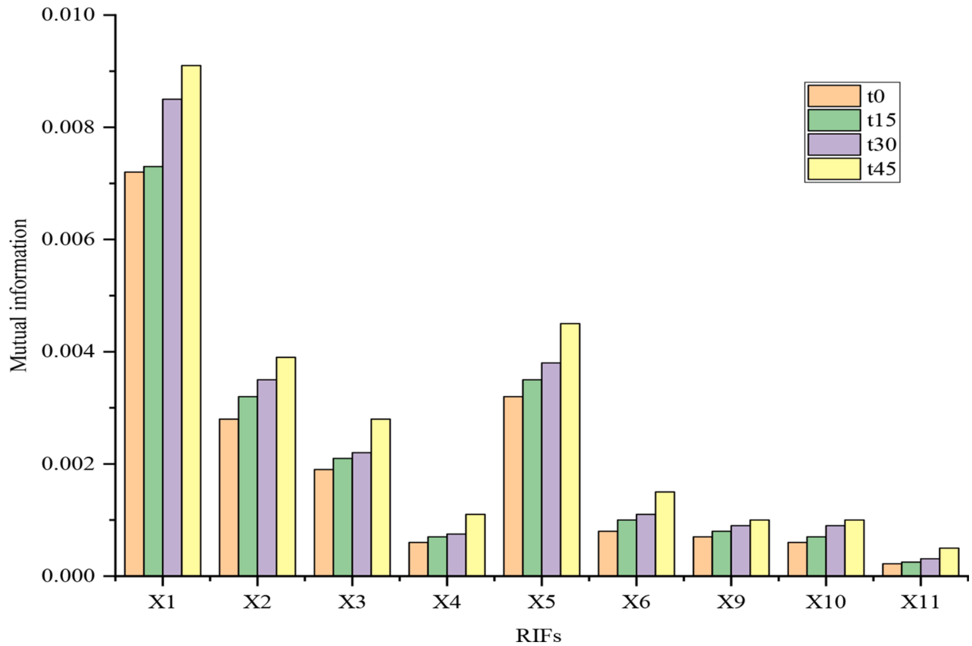

Fig. 9. Sensitivity analysis of RIFs in different time slices.

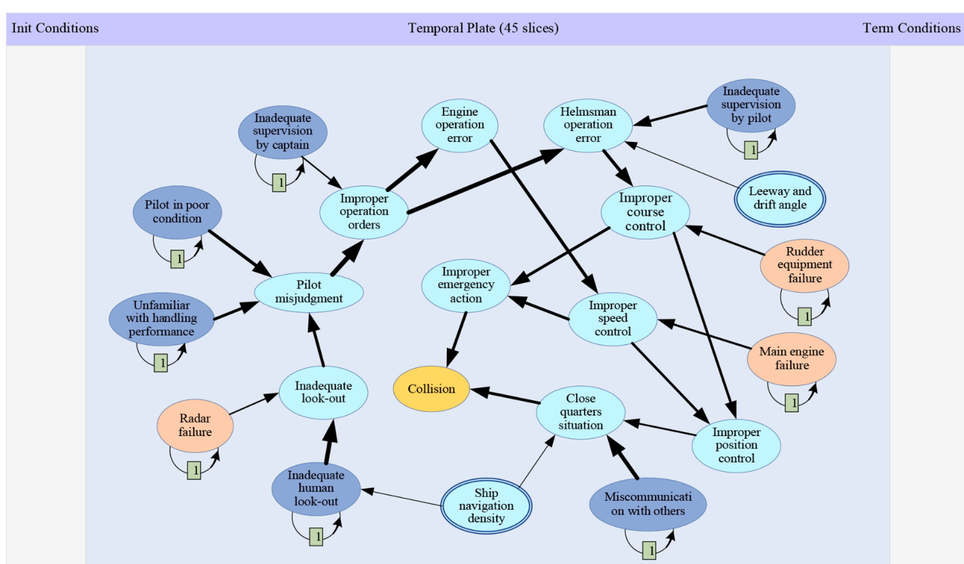

Fig. 10. Strength analysis of RIFs.

are deterministic nodes in the DBN model, so their influence cannot be studied by calculating the mutual information entropy. Inferring the change of the collision risk probability by pairwise combination of the two variable states at time t1, the results are shown in Table 8. Taking the real states of two RIFs at time t1 as the baseline benchmark, the change rates of collision risk probability under several other combinations are ranging −99%~141%. The results show that two environmental RIFs are salient sensitivity factors, in particular, the superimposed influence of them is significant, which is consistent with the results of the previous risk evolution reasoning, so they need particular attention during ship pilotage operations process.

Table 8
Sensitivity analysis of environmental RIFs.

Leeway and drift angle→ Navigable density of ships↓	Large	Medium	Small
Large	4.54E-03 141% ↑	1.88E-03 0%	1.63E-03 −13% ↓
Medium	8.01E-04 −57% ↓	2.96E-04 −84% ↓	2.48E-04 −87% ↓
Small	8.30E-05 −96% ↓	2.91E-05 −98% ↓	2.39E-05 −99% ↓

4.7. Model validation

Model validation is an important methodological step to ensure the reliability, soundness and robustness of any new model structure and parameters, as well as the validity of output results. Along with the above sensitivity analysis and its partial validation on the results, this paper adopts other methods including literature comparison, expert validation, and face validity to test the validity of the developed FRAM-DBN model.

Firstly, the proposed FRAM-DBN model is applied to the ship pilotage process of a container ship in Shanghai Port as a case study, temporal collision risk for ship pilotage process is calculated, while the obtained results are compared with experience-based judgements from experts (see Table 4) to prove that the results are in a harmony with their experience.

Next, the collision risk assessment results are compared with the statistics of collision accidents in this water. The average ship collision probability obtained by the model inference is consistent with the average collision probability of ship pilotage operations in this water in the past five years. Furthermore, the spatio-temporal evolution characteristics of navigation process risk are consistent with Hu et al. [29] (analogous operations scenario in the same water). Both comparative results further reveal that the proposed model can not only capture the risk evolution characteristics of the case ship pilotage operation process, but also deliver reliable results.

As a qualitative analysis method, FRAM is highly dependent on the expertise and experience of the involved analysts. Despite the effort of combining the ACAT method to effectively improve the rigor and consistency of the analysis, the process of system analysis and modeling has still subjectivity and uncertainty at a certain level. To address it, the obtained FRAM (see Fig. 5) and further obtained RIFs (see Table 3) are sent to the five experts (in Table 4) for their evaluation. The results evident that the FRAM model well reflects the collision accident scenarios during the ship piloting operation for the studied case, and the functional modules in the model and their coupling structure are consistent with their experience.

The DBN model proposed based on the FRAM-ACAT analysis results has been validated via face validity. Face validity is proposed by Pitchforth and Mengersen [75] to present model's reliability and validity. The panel of five experts (see Table 4) was invited to evaluate the rationality of the proposed DBN with their experience. Experts were invited to evaluate the model in a chain of the RIFs, the division of their states, and the dependency of the RIFs. The evaluation results against each element under investigation are all satisfactory. In the face validity process, some experts however suggested that more accident risks such as grounding and contact during pilotage operations process should be incorporated into the model in future research given their significant practical insights in the waters.

Finally, a useful means to examine the validity of a subjective built model is to perform sensitivity analysis, sensitivity analysis is a common model validation way for BN to identify the critical RIFs that have a significant impact on collision risk [25]. Through sensitivity analysis (see Section 4.6), the root nodes (factors) in the model all show a certain sensitivity, increase/decrease in the prior probabilities of each parent node may cause a relative increase/decrease in the posterior probability of the collision node. According to the analysis results of the combined changes of environmental factors (see Table 8), the total influence on collision probability variations of two parameters is proven to be always higher than one of the two parameters. These sensitivity analysis results further suggest that the proposed model is in harmony with the Axiom in Zhang et al. [9], thus validating the reliability of the model.

5. Discussions

(1) FRAM-ACAT in systematic risk factors identification

Traditional ship pilotage operational risk analysis is often conducted based on an accident causation theory to obtain RIFs and configure their causal relationships from historical accident data. Historical accident scenarios in the maritime industry have less significant and reference to guide ship pilotage scenario analysis due to the uniqueness of the pilot process. Therefore, the relevant RIFs and their coupling relationships of accident risks in ship pilotage require the development of a new scenario-based risk analysis method. In this paper, the FRAM-ACAT method is used to reveal the risk formation mechanism from the perspective of functional resonance of a ship pilotage operation system. It can not only identify the direct and deep-level RIFs of ship collision risk in a specific ship pilotage scenario, but also effectively capture the nonlinear coupling relationship between RIFs, to realize the systematic risk identification of the ship pilotage process. However, the FRAM-ACAT framework is in nature a qualitative risk analysis method, which will benefit from the incorporation of quantitative reasoning on the risk evolution law of pilotage process.

(2) Maritime risk analysis using BN and DBN

In the field of maritime traffic risk assessment, BN analysis method is widely used. With the help of the logical analysis of accident FTA, the BN topological relationship of the risk factor network in the marine traffic risk system is developed, and the Bayesian probability and conditional probability calculation are used to realize the reasoning, evaluation and monitoring of the marine traffic risk. The existing literature shows that this workflow is effective in coping with deterministic risk systems. Recently, researchers are gaining increasing awareness of incorporating the uncertain impact of stochastic process into marine traffic risk analysis. One of the realistic ways is to develop a discrete DBN, to simulate the uncertain structure of marine RIFs. The traditional discrete DBN has exactly the same structure and parameters of the static BN for each time slice, hence often failing to model the mutation process. From the relationship analysis between parent node and child node in BN, as well as the relationship between various states, this paper proposes an adaptive generation algorithm for parameters. The application of numerical examples generates useful insights in practice.

(3) Risk spatiotemporal evolution in maritime risk analysis

A DBN model of collision risk in a ship pilotage process was constructed according to the risk identification of ship pilotage scenarios. AIS, RADAR data, PSC data, expert judgment were used in a combined way for parameters learning, and the temporal distribution of collision risk in the pilotage operations process was obtained by forward reasoning. Combined with the spatiotemporal correlation information of shipborne AIS, the spatiotemporal evolution characteristics of collision risk are also obtained. The results show that the regional differences of collision risk during ship pilotage process are significant. The collision risks of ship at the entrance of the Beicao channel and the Yuanyuansha warning area are the most significant, while the collision risk of ship sailing in the Yuanyuansha warning zone is more than 100 times greater than that of the straight section in the Beicao channel. Therefore, when a ship navigating in the Yuanyuansha warning area, the pilot should look out with greater caution, cooperate well with the crew and make effective external communication. In addition, the influence of wind and current on ship maneuvering effects should be particularly considered when taking collision avoidance measures in restricted traffic waters.

(4) Sensitivity analysis of RIFs in ship pilotage operations process

Through sensitivity analysis, the influential degree distribution of RIFs in different time slices are obtained. As shown in Fig. 9, the influence of each risk factor increases with time. Combined with mutual information analysis and strength influence analysis, it shows that "Inadequate human look-out" is the most sensitive risk factor in each time slice. The results show that due to the complex and changeable environmental factors and the high density of navigable traffic, the captain and bridge crews should conscientiously perform their lookout duties even if there is a pilot on board. They are obligated to assist the pilot in order to detect potential dangers in time. The second risk factor is "Miscommunication with others", and there may exist complex situations in which ship encounters multiple ships in the pilotage process, so it becomes difficult to make collision avoidance decisions by simply relying on collision avoidance rules. It will become necessary to conduct sufficient and effective communication and coordination with surrounding ships. However, the communication on Very High Frequency (VHF) in dense navigable waters often interferes with each other, and it is necessary for the maritime administration to take corrective measures.

(5) Uncertainty and limitations of the model

The developed model can effectively simulate the temporal evolution of ship collision risk and identify critical RIFs in the ship pilotage operations process according to the real scenarios of ship navigation. Maritime administrative agencies such as VTS and pilot station can formulate targeted risk control measures based on the simulation results, while pilots can also improve the pilot scheme accordingly. However, the model still reveals some uncertainty and limitations.

First, the proposed model focuses on ship collision risks, and does not take into account other accident risk types such as grounding and contact damage. In the future, the Objected Oriented Bayesian Network (OOBN) will be investigated to see if it is a promising solution to tackling all types of accidents in a ship pilotage operations process. Secondly, additional factors such as visibility and waves that have shown less impact on ship collision risk should be analysed when the other types of accidents are investigated. Within this context, risk severity of different accidents could be analyzed and incorporate into the DBN model to extend the risk analysis from single-dimensional to multiple-dimensional perspectives [23].

Thirdly, the first-order Markov hypothesis and stationarity hypothesis well fit the model development and case analysis at this stage of the research. The extent to which they can reflect the operational mechanism of non-stationary random process of ship pilotage should be addressed as their settings affect the accuracy of temporal risk reasoning [26], when the risks of other accident types are analysed. Fourthly, observation data by instruments such as AIS and RADAR is used to obtain the temporal states of environmental factors, which can effectively reduce the influence of information uncertainty and improve the inferential accuracy of scenario risks. In the future, dynamic variables in DBN by means of temporal data monitored through instruments (such as advanced psychological techniques) will improve the acquisition of TPT, to reveal the spatiotemporal evolution of pilotage process risk in real scenarios. It can facilitate the model development and applications in the real world. Finally, risk-based resilience emerges in maritime safety analysis. Resilience is defined as the intrinsic property of the system to respond and adjust the functioning before or after a mishap or disturbance to sustain the normal operational performance of the system [40]. This study highly associates with risk evolution analysis in a dynamic process, which is in principle in line with the risk evolution process across the whole process before and after the occurrence of an accident. The issue on how to incorporate the FRAM-DBN risk evolution model into resilience engineering seems promising, as it possibly enables the ship pilot safety system to adapt to emergent situations and conditions.

6. Conclusion

In this paper, the FRAM-DBN model is proposed to simulate the temporal collision risk during the normal ship pilotage operation process. The tempo-spatial evolution characteristics of ship collision risk are obtained. It is further revealed that ship accidents emerge from nonlinear interconnections of the daily disturbances and variabilities, and high level of variability and uncertainty which arises from this complexity of ship pilotage socio-technical system. It makes contributions from both theoretical and managerial perspectives as follows.

The new theoretical contributions of this paper include

(1) A new hybrid framework combining different methods in a holistic manner to achieve the analysis of ship collision risk spatiotemporal evolution in ship pilotage operations process is proposed.
(2) FRAM and ACAT are integrated together to reveal the complex interaction of system micro-behavior from the perspective of ship pilotage operation real scenarios, to identify the direct and in-depth RIFs of ship collision in the pilotage operations process.
(3) Combined uncertainty methods are used to quantify the CPT and TPT of a DBN in ship pilotage operations risk evolution, which can fully integrate observational evidence, historical data and expert knowledge to solve the problem of uncertainty inference.

The managerial contributions of the case findings are

(1) The collision risk evolution in the ship pilotage operations process shows large regional differences under the coupling effect of multiple factors. It is important to note, that particularly under the superposition effect of wind-current factors and navigation density factors, the functional resonance effect will lead to a surge in collision risk.
(2) This study shows that for effective collision risk management in the ship pilotage operations process, it is not only necessary to pay attention to critical RIFs, but also to formulate corresponding prevention and control measures for the strong coupling between factors.
(3) The integrated methods also suitable for risk evolution analysis in other operational processes such as ship berthing and unberthing, anchoring, etc., and can extend to the process risks evolution in other socio-technical systems such as construction, mining, and road transportation et al.

CRediT authorship contribution statement

Yunlong Guo: Conceptualization, Methodology, Software, Writing – original draft, Validation, Data curation, Writing – review & editing, Supervision. **Yongxing Jin:** Writing – original draft, Writing – review & editing. **Shenping Hu:** Conceptualization, Software, Writing – original draft, Validation, Data curation, Writing – review & editing, Supervision. **Zaili Yang:** Writing – review & editing, Methodology, Validation. **Yongtao Xi:** Data curation, Writing – review & editing. **Bing Han:** Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work is supported by the General Project of Natural Science Research of Jiangsu Province Higher Education Institutions (Grant No. 19KJB580017), the National Key R&D Program of China (Grant No. 2021YFC 2801005), and a European Research Council project (TRUST CoG 2019 864724). The authors thank experts solicited for their valuable suggestions for this study.

References

[1] Wang Y, Wang L, Jiang J, Wang J, Yang Z. Modelling ship collision risk based on the statistical analysis of historical data: a case study in Hong Kong waters. Ocean Eng 2020;197:106869.
[2] Wu L, Jia S, Wang S. Pilotage planning in seaports. Eur J Oper Res 2020;287:90–105.

[3] Basnet S, Bahootoroody A, Chaal M, Valdez Banda OA, Lahtinen J. A decision-making framework for selecting an MBSE language–a case study to ship pilotage. Exp Syst Appl 2022;193:116451.
[4] Khan R, Yin J, Mustafa F, Anning N. Risk assessment for berthing of hazardous cargo vessels using Bayesian networks. Ocean Coast Manag 2021;210:105673.
[5] Feng H, Grifoll M, Yang Z, Zheng P. Collision risk assessment for ships' routeing waters: an information entropy approach with Automatic Identification System (AIS) data. Ocean Coast Manag 2022;224:106184.
[6] Zhang J, Teixeira Â, Soares C, Yan X. Quantitative assessment of collision risk influence factors in the Tianjin port. Saf Sci 2018;110:363–71.
[7] IMO. 1997. Formal safety assessment: trial application to high speed passenger catamaran vessels. Final Report, DE 41/INF.7, submitted by IMO, IMO Sub-Committee on Ship Design and Equipment, 41st Session, Agenda Item 5, London, UK.
[8] IMO. 2018. Revised guidelines for formal safety assessment (FSA) for use in the IMO rule-making process. In: IMO (Ed.), MSC-MEPC.2/Circ.12/Rev.2, London.
[9] Zhang D, Yan X, Yang Z, Wall A, Wang J. Incorporation of formal safety assessment and Bayesian network in navigational risk estimation of the Yangtze river. Reliab Eng Syst Saf 2013;118:93–105.
[10] Yang Z, Wang J, Li K. Maritime safety analysis in retrospect. Marit Policy Manag 2013;40(3):261–77.
[11] Chen P, Huang Y, Mou J, Gelder P. Probabilistic risk analysis for ship-ship collision: state-of-the-art. Saf Sci 2019;117:108–22.
[12] Kujala P, Hanninen M, Arola T, Ylitalo J. Analysis of the marine traffic safety in the Gulf of Finland. Reliab Eng Syst Saf 2009;94(8):1349–57.
[13] Fan C, Wróbel K, Montewka J, Gil M, Wan C, Zhang D. A framework to identify factors influencing navigational risk for maritime autonomous surface ships. Ocean Eng 2020;202:107188.
[14] Zhang M, Zhang D, Goerlandt F, Yan X, Kujala P. Use of HFACS and fault tree model for collision risk factors analysis of icebreaker assistance in ice-covered waters. Saf Sci 2019;111:128–43.
[15] Yang Z, Abujaafar KM, Qu Z, Wang J, Nazir S, Wan C. Use of evidential reasoning for eliciting Bayesian subjective probabilities in human reliability analysis: a maritime case. Ocean Eng 2019;186:106095.
[16] Wu B, Yip TL, Yan X, Soares CG. Review of techniques and challenges of human and organizational factors analysis in maritime transportation. Reliab Eng Syst Saf 2022;219:108249.
[17] Chang CH, Kontovas C, Yu Q, Yang Z. Risk assessment of the operations of maritime autonomous surface ships. Reliab Eng Syst Saf 2021;207:107324.
[18] Wang Y, Chen P, Wu B, Wan C, Yang Z. A trustable architecture over blockchain to facilitate maritime administration for MASS systems. Reliab Eng Syst Saf 2022;219:108246.
[19] Xi Y, Yang Z, Fang Q, Chen W, Wang J. A new hybrid approach to human error probability quantification–applications in maritime operations. Ocean Eng 2017;138:45–54.
[20] Zhang Y, Dong C, Guo W, Dai J, Zhao Z. Systems theoretic accident model and process (STAMP): a literature review. Saf Sci 2022;152:105596.
[21] De Linhares TQ, Maia YL, e Melo PFFF. The phased application of STAMP, FRAM and RAG as a strategy to improve complex sociotechnical system safety. Prog Nucl Energy 2021;131:103571.
[22] Wróbel K, Gil M, Montewka J. Towards a method evaluating control actions in STPA-based model of ship-ship collision avoidance process. In: Proceedings of the ASME 37th International conference on ocean, offshore and arctic engineering OMAE2018; 2018. p. 77790.
[23] Yu Q, Teixeira ÂP, Liu K, Rong H, Soares CG. An integrated dynamic ship risk model based on Bayesian networks and evidential reasoning. Reliab Eng Syst Saf 2021;216:107993.
[24] Gil M, Kozioł P, Wróbel K, Montewka J. Know your safety indicator – A determination of merchant vessels bow crossing range based on big data analytics. Reliab Eng Syst Saf 2022;220:108311.
[25] Fu S, Zhang D, Montewka J, Yan X, Zio E. Towards a probabilistic model for predicting ship besetting in ice in Arctic waters. Reliab Eng Syst Saf 2016;155:124–36.
[26] Khan B, Khan F, Veitch B. A dynamic Bayesian network model for ship-ice collision risk in the Arctic waters. Saf Sci 2020;130:104858.
[27] Baksh A, Abbassi R, Garaniya V, Khan F. Marine transportation risk assessment using Bayesian network: application to Arctic waters. Ocean Eng 2018;159:422–36.
[28] Yu Q, Liu K, Yang Z, Wang H, Yang Z. Geometrical risk evaluation of the collisions between ships and offshore installations using rule-based Bayesian reasoning. Reliab Eng Syst Saf 2021;210:107474.
[29] Hu S, Li W, Xi Y, Li W, Hou Z, Wu J, Han B. Evolution pathway of process risk of marine traffic with the STAMP model and a genetic algorithm: a simulation of LNG-fueled vessel in-and-out harbor. Ocean Eng 2022;253:111133.
[30] Xuan S, Hu S, Li Z, Li W, Li B. Dynamics simulation for process risk evolution on the bunker operation of an LNG-fueled vessel with catastrophe mathematical models. J Mar Sci Eng 2019;7(9):299.
[31] Li Z, Hu S, Zhu X, Gao G, Yao C, Han B. Using DBN and evidence-based reasoning to develop a risk performance model to interfere ship navigation process safety in Arctic waters. Process Saf Environ Prot 2022;162:357–72.
[32] Martins MR, Maturana MC. Application of Bayesian belief networks to the human reliability analysis of an oil tanker operation focusing on collision accidents. Reliab Eng Syst Saf 2013;110:89–109.
[33] Fan S, Davis EB, Yang Z, Zhang J, Yan X. Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. Reliab Eng Syst Saf 2020;203:107070.
[34] Liu K, Yu Q, Yang Z, Wan C, Yang Z. BN-based port state control inspection for Paris MOU: new risk factors and probability training using big data. Reliab Eng Syst Saf 2022;224:108530.
[35] Jiang M, Lu J, Yang Z, Li J. Risk analysis of maritime accidents along the main route of the maritime silk road: a Bayesian network approach. Marit Policy Manag 2020;47(6):815–32.
[36] Özaydın E, Fışkın R, Uğurlu Ö, Wang J. A hybrid model for marine accident analysis based on Bayesian network (BN) and association rule mining (ARM). Ocean Eng 2022;247:110705.
[37] Li KX, Yin J, Bang HS, Yang Z, Wang J. Bayesian network with quantitative input for maritime risk analysis. Transportmetrica A 2012;10(2):89–118.
[38] Song G, Khan F, Wang H, Leighton S, Yuan Z, Liu H. Dynamic occupational risk model for offshore operations in harsh environments. Reliab Eng Syst Saf 2016;150:58–64.
[39] Chaal M, Bahootoroody A, Basnet S, Valdez Banda OA, Goerlandt F. Towards system-theoretic risk assessment for future ships: a framework for selecting risk control options. Ocean Eng 2022;259:111797.
[40] Qiao W, Ma X, Liu Y, Deng W. Resilience evaluation of maritime liquid cargo emergency response by integrating FRAM and a BN: a case study of a propylene leakage emergency scenario. Ocean Eng 2022;247:110584.
[41] Fu S, Yu Y, Chen J, Xi Y, Zhang M. A framework for quantitative analysis of the causation of grounding accidents in Arctic shipping. Reliab Eng Syst Saf 2022;226:108706.
[42] Ung ST. Navigation risk estimation using a modified Bayesian network modeling-A case study in Taiwan. Reliab Eng Syst Saf 2021;213:107777.
[43] Pan Y, Zhang L, Li Z, Ding L. Improved fuzzy Bayesian network-based risk analysis with interval-valued fuzzy sets and D–S evidence theory. IEEE Trans Fuzzy Syst 2020;28(9):2063–77.
[44] Qian H, Zhang R, Zhang Y. Dynamic risk assessment of natural environment based on dynamic Bayesian network for key nodes of the Arctic northwest passage. Ocean Eng 2020;203:107205.
[45] Dabrowski JJ, Villiers JP. Maritime piracy situation modelling with dynamic Bayesian networks. Inf Fusion 2015;23:116–30.
[46] Li Z, Hu S, Gao G, Yao C, Fu S, Xi Y. Decision-making on process risk of Arctic route for LNG carrier Via dynamic Bayesian network modeling. J Loss Prevent Process Ind 2021;71:104473.
[47] He R, Li X, Chen G, Wang Y, Jiang S, Zhi C. A quantitative risk analysis model considering uncertain information. Process Saf Environ Prot 2018;118:361–70.
[48] Hollnagel E. Barriers and accident prevention. Aldershot (UK): Ashgate Publishing; 2004.
[49] De Carvalho PVR. The use of Functional Resonance Analysis Method (FRAM) in a mid-air collision to understand some characteristics of the air traffic management system resilience. Reliab Eng Syst Saf 2011;96:1482–98.
[50] Patriarca R, Di Gravio G, Woltjer R, Costantino F, Praetorius G, Ferreira P, Hollnagel E. Framing the FRAM: a literature review on the functional resonance analysis method. Saf Sci 2020;129:104827.
[51] Salihoglu E, Beşikçi E. The use of Functional Resonance Analysis Method (FRAM) in a maritime accident: a case study of Prestige. Ocean Eng 2021;219:108223.
[52] Saldanha MCW, Carvalho RJM, Arcuri R, Amorim AG, Vidal MCR, Carvalho PVR. Understanding and improving safety in artisanal fishing: a safety-II approach in raft fishing. Saf Sci 2020;122:104522.
[53] Li W, Zhang L, Liang W. An accident causation analysis and taxonomy (ACAT) model of complex industrial system from both system safety and control theory perspectives. Saf Sci 2017;92:94–103.
[54] Li W, He M, Sun Y, Cao Q. A proactive operational risk identification and analysis framework based on the integration of ACAT and FRAM. Reliab Eng Syst Saf 2019;186:101–9.
[55] Patriarca R, Gravio GD, Costantino F. A Monte Carlo evolution of the Functional Resonance Analysis Method (FRAM) to assess performance variability in complex systems. Saf Sci 2017;91:49–60.
[56] Kaya GK, Ozturk F, Sariguzel EE. System-based risk analysis in a tram operating system: integrating Monte Carlo simulation with the functional resonance analysis method. Reliab Eng Syst Saf 2021;215:107835.
[57] Yu M, Erraguntla M, Quddus N, Kravaris C. A data-driven approach of quantifying function couplings and identifying paths towards emerging hazards in complex systems. Process Saf Environ Prot 2021;150:464–77.
[58] Zinetullina A, Yang M, Khakzad N, Golman B, Li X. Quantitative resilience assessment of chemical process systems using functional resonance analysis method and dynamic Bayesian network. Reliab Eng Syst Saf 2021;205:107232.
[59] Špačková O, Straub D. Dynamic Bayesian network for probabilistic modeling of tunnel excavation processes. Comput Aided Civ Inf 2012;28(1):1–21.
[60] Guo X, Ji J, Khan F, Ding L, Tong Q. A novel fuzzy dynamic Bayesian network for dynamic risk assessment and uncertainty propagation quantification in uncertainty environment. Saf Sci 2021;141:105285.
[61] Li J, Li H, Wang F, Cheng ASK, Yang X, Wang H. Proactive analysis of construction equipment operators' hazard perception error based on cognitive modeling and a dynamic Bayesian network. Reliab Eng Syst Saf 2021;205:107203.
[62] Zhang Y, Cai B, Liu Y, Jiang Q, Li W, Feng Q, Liu Y, Liu G. Resilience assessment approach of mechanical structure combining finite element models and dynamic Bayesian networks. Reliab Eng Syst Saf 2021;216:108043.
[63] Shi J, Gao X, Wang Q. To generate the parameters of the structure varied discrete dynamic Bayesian network adaptively. J Syst Eng Electron 2008;30:1836–9 (In Chinese).
[64] Wang Y, Qin T, Li B, Sun X, Li Y. Fire probability prediction of offshore platform based on dynamic Bayesian network. Ocean Eng 2017;145:112–23.

[65] Chang Y, Zhang C, Shi J, Li J, Zhang S, Chen G. Dynamic Bayesian network based approach for risk analysis of hydrogen generation unit leakage. Int J Hydrog Energy 2019;44:26665–78.

[66] Uddin MI, Awal ZI. Systems-theoretic approach to safety of inland passenger ship operation in Bangladesh. Saf Sci 2020;126:104629.

[67] Oraith H, Davis EB, Yang Z, Matellini B. An evaluation of the effects of human factors on pilotage operations safety. J Mar Sci Appl 2021;20:393–409.

[68] Hänninen M, Kujala P. Influences of variables on ship collision probability in a Bayesian belief network model. Reliab Eng Syst Saf 2012;102:27–40.

[69] Szlapczynski R, Szlapczynska J. Review of ship safety domains: models and applications. Ocean Eng 2017;145:277–89.

[70] Fiskin R, Nasiboglu E, Yardimci MO. A knowledge-based framework for two-dimensional (2D) asymmetrical polygonal ship domain. Ocean Eng 2020;202:107187.

[71] Pietrzykowski Z, Wielgosz M. Effective ship domain – Impact of ship size and speed. Ocean Eng 2021;219:108423.

[72] Ugurlu H, Cicek I. Analysis and assessment of ship collision accidents using fault tree and multiple correspondence analysis. Ocean Eng 2022;245:110514.

[73] Fowler TG, Sorgard E. Modeling ship transportation risk. Risk Anal 2000;20(2):225–44.

[74] Wang L, Yang Z. Bayesian network modelling and analysis of accident severity in waterborne transportation: a case study in China. Reliab Eng Syst Saf 2018;180:277–89.

[75] Pitchforth J, Mengersen K. A proposed validation framework for expert elicited Bayesian networks. Exp Syst Appl 2013;40(1):162–7.