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Data-driven Bayesian network for risk analysis of global maritime accidents

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ABSTRACT

Maritime risk research often suffers from insufficient data for accurate prediction and analysis. This paper aims to conduct a new risk analysis by incorporating the latest maritime accident data into a Bayesian network (BN) model to analyze the key risk influential factors (RIFs) in the maritime sector. It makes important contributions in terms of a novel maritime accident database, new RIFs, findings, and implications. More specifically, the latest maritime accident data from 2017 to 2021 is collected from both the Global Integrated Shipping Information System (GISIS) and Lloyd's Register Fairplay (LRF) databases. Based on the new dataset, 23 RIFs are identified, involving both dynamic and static risk factors. With these developments, new findings and implications are revealed beyond the state-of-the-art of maritime risk analysis. For instance, the research results show ship type, ship operation, voyage segment, deadweight, length, and power are among the most influencing factors. The new BN-based risk model offers reliable and accurate risk prediction results, evident by its prediction performance and scenario analysis. It provides valuable insights into the development of rational accident prevention measures that could well fit the increasing demands of maritime safety in today's complex shipping environment.

1. Introduction

The rapid development of the shipping industry stimulates global trade prosperity, which also poses challenges to maritime safety [1]. Shipping has the characteristics of large transportation capacity, long haulage distance and low cost, which contribute to its ability to carry more than 90% of the international trade in volume [2,3]. However, the increase in maritime transportation demand has led to the rapid development of large-scale and high-speed ships, high maritime traffic density, and intense traffic situations [4]. In addition, due to the impact of complex marine navigation environments and severe weather, maritime accidents often lead to serious consequences, including channel blockage, economic loss, environmental pollution, and/or even death [5]. For example, the giant container ship 'Ever Given' ran aground in the Suez Canal on 23rd Mar. 2021 due to strong winds and human error, which caused a disruption in the canal, a serious backlog of ships, and losses of hundreds of billions of dollars in trade [6]. Therefore, it is particularly imminent to prevent maritime accidents and ensure safety at sea for the sustainable development of the shipping industry, along with the primary goal of the International Maritime Organization (IMO).

The relevant studies in the existing literature have shown that the task is challenging as the safety of maritime transport is affected by (1) a combination of factors of high uncertainty such as ship conditions, environmental conditions, human error, and management issues [7] and (2) dynamic features of the factors whose impact on maritime safety changes with time. To address them, it is necessary to collect and investigate the newest data derived from recent maritime accidents, analyze the causes of the accidents, extract the key risk influential factors (RIFs) in different scenarios, and then predict the associated risk. Although classical risk analysis methods (e.g. probabilistic risk analysis) have been widely applied in the maritime industry, they often fail to address inherent problems in maritime risk analysis, such as incomplete historical data and complicated interdependency among the risk factors. These problems stimulate the development of advanced risk analysis methods using primary uncertainty theories (e.g. fuzzy logic (FL), the D-S theory, and the Bayesian probabilistic theory).

Among the advanced maritime risk analysis methods, a Bayesian network (BN) has attracted much attention due to its ability to capture RIFs and their interrelationships efficiently in recent years. Fan et al. [8] selected the Naïve Bayesian network (NBN) to model maritime accident risk analysis and extracted 16 RIFs based on the 161 accident reports collected from 2012 to 2017. Wang and Yang [9] applied an augmented naïve BN (ABN) method to model the waterway accident data and analyze the RIFs related to the severity based on the data collected from

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China's Maritime Safety Administration (MSA). 229 accident reports with 350 vessels were screened from 1979 to 2015 to identify the 20 RIFs to construct the risk model. Jiang and Lu [10] proposed a dynamic Bayesian network (DBN) model for assessing dynamic contingencies in Indian Ocean sea lanes based on the incident data from 2007 to 2018. Zhao et al. [11] applied a Bayesian-based network training method to study the potential causes of maritime accidents for autonomous ships in the Yangtze River based on the collected 160 accident reports from the China Maritime Safety Administration from 2013 to 2019. 19 RIFs were recognised from the accident information. Although showing some attractiveness, these studies have revealed their applications in a regional water and/or without a full set of all relevant RIFs because of the data limitations.

The Marine Casualties and Incidents in the Global Integrated Shipping Information System (GISIS) database of the IMO is the world's most authoritative accident investigation dataset. Lloyd's Register Fairplay (LRF) database stores the official global static data of ships. In this paper, we develop a new maritime accident dataset with all the datasets containing comprehensive records against all the IMO regulated RIFs from the GISIS dataset and survey reports for the 2017–2021 period. In the process of the dataset development, the incompleted and missing ship-related data in the GISIS database are complemented by the LRF database. Along with the new maritime accident database, the other main contributions of this paper are as follows:

(1) The latest maritime accident data from 2017 to 2021 is collected from the GISIS and LRF to develop a new accident database in which each dataset contains comprehensive information on all the relevant static and dynamic RIFs.
(2) By incorporating all the IMO regulated RIFs into a new BN-based risk analysis model, it improves the accuracy of maritime risk prediction and diagnosis analysis.
(3) Thanks to the comprehensive datasets, all the RIFs are, for the first time, defined by the multiple states recommended by the IMO. It aids in improving the standardisation of maritime risk analysis, which in the current literature is presented in diversified ways and hammers the comparative analysis and benchmarking across different analysis results
(4) The development of a data-driven BN model based on global maritime accidents stimulates maritime accident analysis from a global perspective. The result can be used as a benchmark for regional maritime accident analysis.
(5) It explores the newest characteristics of marine accidents through various sensitivity and scenario analysis. The results can guide the rational development of new accident prevention measures that fit today's complex maritime environment.

The rest of the paper is structured as follows. Section 2 describes a detailed literature review of maritime accident research and the state-of-the-art of using BN in maritime risk analysis. Section 3 presents the development of a new accident database and the identification of the RIFs. The methodology consisting of BN structure learning, model validation, and sensitivity analysis is presented in Section 4. Section 5 reveals the results and discusses the impact of the most important RIFs through sensitivity analysis for drawing useful implications. It also estimates accident risks in different situations through scenario simulation. Finally, Section 6 concludes the paper.

2. Literature review

2.1. Studies of maritime risk analysis

To assess risks and ensure maritime safety, a systematic and structured methodology, Formal Safety Assessment (FSA), was proposed by the IMO. Ship conditions, organisational management, hardware equipment, and environmental factors are taken into account in the FSA method to provide reference and support for maritime stakeholders to make decisions [9]. Within the context of the FSA methodology, a lot of maritime risk studies, including qualitative and quantitative assessments, have been carried out worldwide [12]. Qualitative assessments provide detailed observations by analysing small samples. The commonly used qualitative evaluation methods in shipping risk analysis include Functional Resonance Analysis Method (FRAM), Root Cause Analysis (RCA) and Risk Rating Scales, etc. In particular, qualitative methods such as Human Factors Analysis and Classification System (HFACS) and Accident Analysis Mapping (AcciMap) are used to analyze human factors in maritime accidents. Arslan and Turan [13] investigated the marine casualties for shipping safety based on a Strength, Weakness, Opportunity and Threat (SWOT) analysis and AHP (analytic hierarchy process) method at the Strait of Istanbul. Chen et al. [14] utilized an HFACS method to investigate and classify human factors in maritime accidents. Salihoglu and Beşikçi [15] applied a FRAM method to assess the risk of shipping operations qualitatively. However, qualitative assessment methods could not quantify risks, thus often being criticised for their reliability and validity [2].

To address these drawbacks, scholars have used Quantitative Risk Assessments (QRA) to quantitatively measure the causal relation between marine accidents and the relevant influential factors. Many QRA models have been proposed and widely used in the maritime safety field, such as FL, Evidence Reasoning (ER), Event Tree Analysis (ETA), Fault Tree Analysis (FTA) and BN [16,17]. Balmat et al. [18] proposed a fuzzy approach to evaluate maritime risk based on a decision system. Zhang et al. [19] adopted a Belief Rule Base (BRB) methodology to evaluate the safety management performance of the Maritime Safety Administration (MSA). Raiyan et al. [20] utilized an ETA method to explore the impact of a single risk factor or a combination of different factors on accident occurrence. Wu et al. [21] put forward a disposal method for ships without command by incorporating ER and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in emergency decision-making. QRA methods can effectively deal with the uncertainty related to risk. However, the lack of maritime accident data impedes QRA applications, and as a result, some influencing factors have to be overlooked in the analysis. Therefore, the hybrid methods that combine qualitative and quantitative evaluation are proposed and applied to investigate the risk of maritime transportation [7]. For instance, Kum and Sahin [22] explored previous maritime accidents in the Arctic region, applied an RCA method to explain the causes, and applied a fuzzy FTA to make suggestions to decrease the probability of maritime accidents. Sotiralis et al. [23] proposed a method based on the Technique for Retrospective and Predictive Analysis of Cognitive Errors (TRACEr) and BN to explore human factors in the quantitative analysis of ship operational risk.

Among all the QRA methods used in maritime transport, BN shows unique advantages with its powerful modelling capabilities on data tolerance and bi-directional risk diagnosis and prediction analysis. Compared to FL and ER, BN is superior in modelling causal relationships between the influential factors [2]. Compared with FTA, BN can tackle multiple-state variables and multiple outputs. In addition, compared to the other QRA methods, BN has shown its capacity to model and accommodate human and organisational factors together with other RIFs [24]. These characteristics make BN a suitable method for maritime accident modelling in this study.

2.2. BN in maritime risk analysis

In this section, the advantages of BN in risk modelling are further demonstrated by a systematic review of its applications in maritime accident/risk analysis. Hänninen [25] conducted an in-depth study on the benefits and challenges of BN applied to maritime transport risk assessment. The results showed that BN significantly fits maritime safety management and decision-making. BN can identify the most significant influential factors and explicitly reveal the probabilistic dependency and causal relationship among RIFs. It also has the ability to forward analysis and reverse reasoning, incorporate new information or evidence to update risk inference, and deal with missing data [7]. Therefore, BN has witnessed increasing popularity in the field of maritime safety, including illustrative studies on inland waterway congestion [26], pirate attack risk analysis [27], and marine accident risk analysis in the Arctic water [28], etc.

When applying BN in maritime accident analysis, the first step is to establish a BN structure. Generally, literature review, expert knowledge, data learning, or their combination are the main methods for BN structure learning [16]. Bouejla et al. [29] utilised qualitative knowledge provided by maritime experts and the data from the IMO to construct a BN structure to assess the risk of piracy attacks on ships and oil fields. Pristrom et al. [27] built a BN model based on the GISIS data and expert judgement to estimate the probability of a ship being hijacked by pirates in the West Indies or East Africa. Zhang et al. [16] integrated statistical data and expert knowledge to establish a BN model for predicting the consequences of maritime accidents in Tianjin Port. Expert knowledge remains an essential data source for maritime accident modelling when essential data becomes unavailable or incomplete from relevant investigations [30]. However, expert knowledge is argued to be subjective and uncertain [5].

To avoid the subjectivity and incompleteness introduced by subjective data in BN modelling, many scholars have developed data-driven BN for maritime risk analysis. The results of these studies show that the data-driven BN is an effective tool for maritime accident prevention and safety management [31]. There are a number of algorithms for the data-driven approach, such as Naïve Bayesian Networks (NBN), Augmented naive Bayesian Networks (ABN), K2 algorithm, and TAN. Fan et al. [8] applied NBN to construct a network model to stimulate the interdependence among risk factors and quantify the impact of different factors on various maritime accidents. However, an NBN model requires that the influential factors are independent, which is not in line with the actual situation of maritime accidents. Wang and Yang [9] selected an ABN model through a comparative study with the NBN model to analyze the key risk RIFs affecting the severity of waterway accidents. However, the network structure of this model was relatively complex, requiring the artificial adjustments of unreasonable causal relationships among RIFs. Friedman et al. [32] pointed out that TAN is superior to NBN. TAN not only maintains the robustness and computational simplicity of NBN but also improves the result accuracy. Among data-driven network construction methods, the TAN method has been shown to be more competitive and accurate [24,33,34]. Therefore, this study extends the TAN method by the integration of information entropy to construct a BN model of maritime accidents. The new model can avoid subjective inferences, explore the hidden cause among different RIFs, and improve risk prediction accuracy.

Data-driven BN requires a large amount of historical accident data. Although the existing marine accident databases provide a large number of datasets, many of them only focus on a certain selected value for specific purposes they serve [5], and hence none has comprehensive maritime accident data against all the dynamic and static information of the RIFs by the IMO. The maritime accident investigation reports provide navigation conditions, environmental information, human operations and causes of an accident, while indicating in detail the potential risks and causal relationships among various factors [24]. However, there are few studies using accident reports for accident analysis because extracting data from each report is costly. Furthermore, the number of accident reports containing comprehensive information on all the RIFs is scanty, often resulting in cross-references among multiple reports from different sources. It is evident by the fact that (1) the existing research using marine accident reports replies on a selected number of RIFs due to the limitation of the data availability, and (2) in most cases, the research scopes are constrained to a national/regional area.

2.3. Our contribution to maritime accident risk analysis

In this work, we combine the two most established maritime accident databases (i.e. GISIS and LRF) to develop a new database to address the data incompleteness issues in the existing studies. In total, 402 accident data records are derived using the criteria against which every single accident has to be complete and comprehensive. Meantime, each dataset must contain all the information against the regulated RIFs by the IMO. All the data also have to be recent and fall in the period of 2017–2021 to capture the latest characteristics of maritime accidents. The new data-driven BN complements the previous studies in the field by investigating all the 23 RIFs by the IMO and their joint impact on maritime accidents for the first time. Because of the amount of data obtained, this paper does not necessarily compromise the abstraction of the states used to describe all the 23 RIFs. In other words, all the states/grades used to model each RIF are kept consistent with the ones by the IMO, which will significantly stimulate the standardisation of maritime risk analysis and result benchmarking. Finally, from the perspective of practical implications, the new findings from this paper aid in capturing the evolution of maritime accident risk characteristics in the recent five years, which is, to the authors' best knowledge, absent from the existing literature.

3. Data collection and processing

3.1. Data collection

This study establishes a new maritime accident database for the period 2017–2021 based on the IMO GISIS and LRF databases. The maritime casualties and incidents information is collected and described under the requirements of the IMO, while some complete investigation reports from the IMO are also provided and listed in the GISIS casualty module. among them, the incident information contains the time and place of an accident, the involved ships and a simple description of the cause, etc. Meantime, the accident reports contain more detailed information on the ship's navigation, the external environmental condition, the process of the accident, and the root cause analysis. Furthermore, the normalised ship data provided by the LRF are used to complete the missing ship information (i.e. ship type, ship age, hull construction, hull type) in the IMO GISIS accident database. The ship's Maritime Mobile Service Identity (MMSI) number and IMO number are used to bridge the relevant information from the two different databases to ensure the consistency and accuracy of the collected data.

The original accident database is generated through a comprehensive statistical analysis of marine accidents recorded in the above databases. The data records are collected from the IMO GISIS database. The ship type, hull type, ship age, length, breadth, gross tonnage, deadweight, and hull construction are incomplete in many records. Then, the static information is searched from the LRF database based on the MMSI and IMO number of each ship to complete the data. The completed data is also checked in the LRF database to ensure their accuracy, integrity, and validity. It costs six months for data collection and verification before further data screening. In total, 1105 accident data records are extracted from the IMO GISIS database from 1st Jan. 2017 to 31st Dec. 2021 against the two criteria set in Section 2.3. The detailed data screening process is shown below.

Step 1. Data cleansing.

Accidents involving fishing vessels contain incomplete data, and in some cases, only ship static information is recorded. It is difficult, if not impossible, to use other accident databases to complement such accident reports against all 23 RIFs. Hence they are removed from our newly developed database. Similarly, after a careful investigation, accident reports involving domestic ferries and navy ships are also removed for the same reason. Finally, 462 accident data records are reserved after the data cleansing.

Step 2. Data completion.

For the remaining 462 accident records, the LRF database is applied

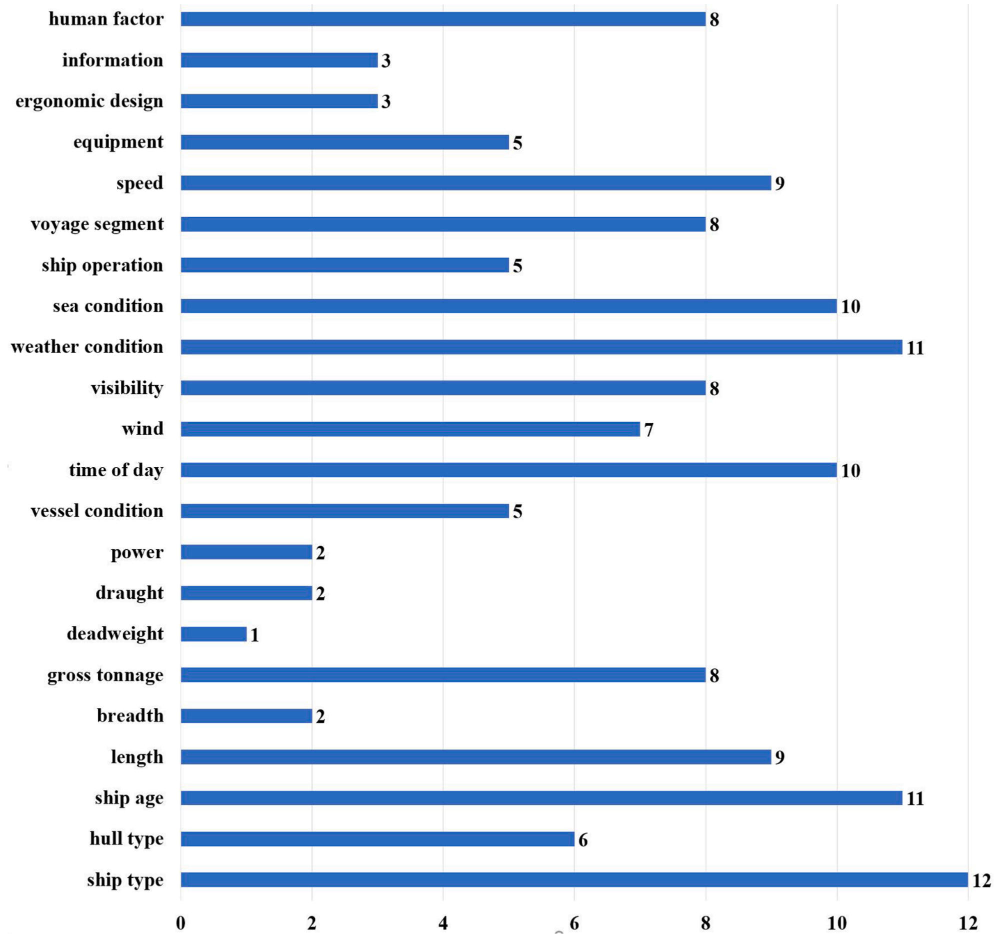

Fig. 1. Frequency of RIFs in the retrieved literature.

to supplement the missing data when necessary, such as the information on the ship type, hull type, ship age, breadth, length, gross tonnage, deadweight, and hull construction based on IMO number and MMSI. Eventually, 428 accident data records have a full set of data supporting all the identified RIFs in Section 3.2.

Step 3. Data screening.

To ensure integrity and validity, data screening is further conducted to remove inaccurate data by manually checking each remained record and report. Accident records that fail to explain the cause of the involved accident, ship equipment, and environmental information are discarded. At last, 402 accident records are reserved in the new database in this study.

3.2. *RIF identification*

Factors affecting the safety of maritime transport are defined as RIFs. Based on the constructed maritime accident database, this paper identified RIFs using the relevant literature and existing marine accident records guidance from the IMO. The relevant literature is obtained by searching the keywords ‘Bayesian network’ and ‘Maritime accident’ on the Web of Science. There are 129 related journal papers found by the research. After further screening of their abstracts and contents, 16 typical journal papers that described the risk factors are selected for further analysis. Then, the RIFs are analyzed against each of the 16 retrieved results, and the visualisation of all the 22 RIFs is shown in Fig. 1. It is evident that ship type (12), ship age (11), weather condition (10), length (9), time of the day (9), sea condition (9), gross tonnage(8) and ship speed (8) are the top eight RIFs in the previous research.

To better understand the RIF difference in the previous studies, the sources of different RIFs based on the retrieved results and the new database are presented and compared. Furthermore, according to the new maritime accident dataset, 23 RIFs are finally identified and listed in Table 1 by the frequency of occurrence of each risk factor. As shown in Table 1, numbers 1–23 denote the 23 RIFs, ‘A’ means this RIF is applied in the related reference, ‘GL’ indicates that the RIF data is from the IMO GISIS and LRF databases. ‘G’ expresses that the RIF data is only from the IMO GISIS database. It further reveals the necessity and effectiveness of the combination of the IMO GISIS and LRF databases. The overlaps and gaps among the RIFs highlight the new contributions of this paper in the sense that it pioneers a comprehensive BN-based maritime risk model without the need to overlook some RIFs due to data limitation. Compared with the previous studies, the RIFs in this study consist of a new variable (i.e. hull construction). Hull construction is deemed as a risk factor for maritime accidents for the first time as it closely links with RIFs such as ship type and accident type. It is generally divided into double hull, single hull, and double bottom. Double-hull vessels tend to have better stability and manoeuvrability than single-hull vessels [35].

After identifying the RIFs, the previous studies in the field normally need to simplify the definition of their states in order to reduce the high data demand in the process of quantifying their interdependencies (e.g. conditional probability tables – CPT in BN). Obviously, it will make it difficult to compare and benchmark the risk analysis results across different waters or periods of time. For example, for the ‘voyage segment’ of an accident, the IMO gives a more detailed classification, including anchorage, archipelagos, at berth, canal, channel, coastal waters, inland waters, open sea, port, port approach, and river. The new database records detailed ship type information for the variable ‘ship type’. To make full use of the information in the data, we add two new

Table 1
The sources of RIFs based on the retrieved results and the novel dataset.

Refs. and database	RIFs 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Total
[8]	A	A	A	A		A					A	A			A	A	A	A	A	A	A	A		15
[24]	A	A	A	A		A					A	A			A	A	A	A	A	A	A	A	A	16
[36]	A	A	A	A		A					A	A			A	A	A	A	A	A	A	A	A	16
[2]	A		A									A	A	A	A	A		A	A					9
[31]	A	A	A	A	A	A		A	A			A		A	A		A		A				A	14
[16]	A			A								A						A						4
[11]	A	A	A	A	A	A		A	A			A		A	A		A		A				A	14
[37]				A			A						A			A			A					5
[9]	A	A	A	A		A							A	A	A			A	A				A	11
[38]												A			A	A				A				4
[7]	A		A									A	A	A	A			A	A				A	9
[39]			A								A									A			A	4
[33]	A		A	A		A						A	A	A		A								8
[10]													A	A	A	A								4
[40]	A		A			A										A		A						5
[41]	A										A		A	A	A	A							A	7
Data sources	GL	GL	GL	GL	GL	GL	GL	GL	GL	GL	G	G	G	G	G	G	G	G	G	G	G	G	G	23
Total	14	8	13	11	4	10	3	4	4	2	6	11	8	9	12	11	6	9	10	6	4	4	9	

Note: 1. ship type; 2. hull type; 3. ship age; 4. length; 5. breadth; 6. gross tonnage; 7. deadweight; 8. draught; 9. power; 10. hull construction; 11. vessel condition; 12. time of day; 13. wind; 14.visibility; 15.weather condition; 16. sea condition; 17. ship operation; 18. voyage segment; 19. speed; 20. equipment; 21. ergonomic design; 22. information; 23. human factor. 'A' means this RIF is applied in the related reference. 'GL' indicates that the data is from both the IMO GISIS and LRF databases. 'G' expresses that the data is only from the IMO GISIS database.

Table 2
Definition and Status of RIFs.

Number	RIFs	Description	States
Ship-related factors			
1	Ship type	Bulk carrier, cargo ship, container ship, dredger, fishing ship, offshore ship, passenger ship, RORO, tanker or chemical ship, tug, others	1,2,3,4,5,6,7,8, 9,10,11
2	Hull type	Aluminium alloy, composite materials, GRP, light alloy, steel, wood, NA	1,2,3,4,5,6,7
3	Ship age (years)	(0,5], [6,10], [11,15], [16,20], >20, NA	1,2,3,4,5,6
4	Length (meters)	(0,100], (100,200], >200	1,2,3
5	Breadth (meters)	(0,20], (20,30], (30,40], >40	1,2,3,4
6	Gross tonnage (GT)	(0,3000], (3000,10,000], (10,000,20,000], >20,000	1,2,3,4
7	Deadweight (DWT)	(0,5000], (5000,15,000], (15,000,30,000], >30,000	1,2,3,4
8	Draught (meters)	(0,6], (6,9], >9	1,2,3
9	Power (kW)	(0,3000], >3000	1,2
10	Hull construction	Double bottom, double hull, single hull	1,2,3
11	Vessel condition	Good condition of ships or the vessel condition has nothing to do with the accident; Poor condition of ships (e.g. ship design errors, failure of ship equipment)	good, bad
Environment-related factors			
12	Time of day	Day (07:00 to 19:00), night (other)	day, night
13	Wind (Beaufort scale)	0 to 5, greater than 6	high, low
14	Visibility (nm)	2 or less, greater than 2	good, bad
15	Weather condition	Good or bad, considering wind, rain, fog, visibility, and extreme weather	good, bad
16	Sea condition	Good or bad, considering falling or rising tide, current, waves, and sea state	good, bad
Navigation-related factors			
17	Ship operation	At anchor, fishing, loading/ unloading, on passage, manoeuvring, pilotage, towing, others	1,2,3,4,5,6,7,8
18	Voyage segment	anchorage, archipelagos, at berth, canal, channel, coastal waters, inland waters, open sea, port, port approach, river	1,2,3,4,5,6,7,8,9,10,11
19	Ship speed (knots)	Low (0–6), middle (6–12), high (>12)	low, middle, high
20	Equipment	Equipment on board is in good condition and operated correctly; Failure or incorrect operation of equipment on board (such as failure of propulsion machinery, failure of electrical installation, the alarm system turned off or not noticed, etc.)	good, bad
21	Ergonomic design	Friendly ergonomic design or has nothing to do with the accidents; Unfriendly ergonomic	good, bad

(*continued on next page*)

Table 2 (*continued*)

Number	RIFs	Description	States
Ship-related factors			
		design (such as poor bridge ergonomics, insufficient stability, etc.)	
22	Information	Providing updated and effective information; Lake of updated and effective information (such as inadequacy of navigational equipment, poor and unreliable chart data, failure to send signals or respond appropriately, etc.)	good, bad
Human-related factors			
23	Human factor	Human factors have nothing to do with the accident; Human violations or errors (such as fatigue, stress, error in judgement, lack of familiarity or training, management and supervision, etc.)	no, yes

types, offshore ships (including supply ships, drill ships, production platforms and diving vessels, etc.) and dredgers based on common ship types. In addition, the existing norms, such as Beaufort Wind Scales, Sea State Scales, and Visibility Scales, are used to define the status of environment-related RIFs. Finally, the definitions of all RIFs in this study and their status are shown in Table 2.

Further, the effect of the 23 RIFs on different types of maritime accidents will be investigated. The total accident numbers of the accidents due to 'electrical problems' and 'falling into cargo' are very small, and lack critical mass in this study when compared to the other ten accident types. The two accident types are therefore merged and presented as 'others', which forms the new classification of 11 accident types (i.e. capsize, collision, grounding, contact/crush, fire/explosion, flooding, occupational accident, overboard, ship/equipment damage, sinking, and others (electrical problems, falling into cargo, etc.).

4. Methodology

Maritime risk analysis studies using BN are usually conducted through several established steps, including data collection, variable identification, structure learning, model validation and sensitivity analysis [42]. The methodology in this paper is not an exception, consisting of four parts: database generation, model construction, model validation, and model output, as shown in Fig. 2. However, the new methodological contributions are seen from the detailed supporting methods and analysis in each step.

The BN structure learning is used for model construction to create the network. Model validation includes two important parts: sensitivity analysis and model evaluation. Three indexes are applied to analyze the sensitivity of the constructed model, including mutual information, joint probability, and True Risk Influence (TRI). Four different model validation methods (i.e. correctness, prediction performance, consistency, and real case verification) are applied to test the effectiveness of the proposed model. Finally, the model output provides valuable implications for preventing maritime accidents and reducing maritime risk.

The methodological contributions include (1) generating a new database in step 1; (2) taking into account new RIFs and their states in step 2; (3) proposing novel prediction and real case validation methods

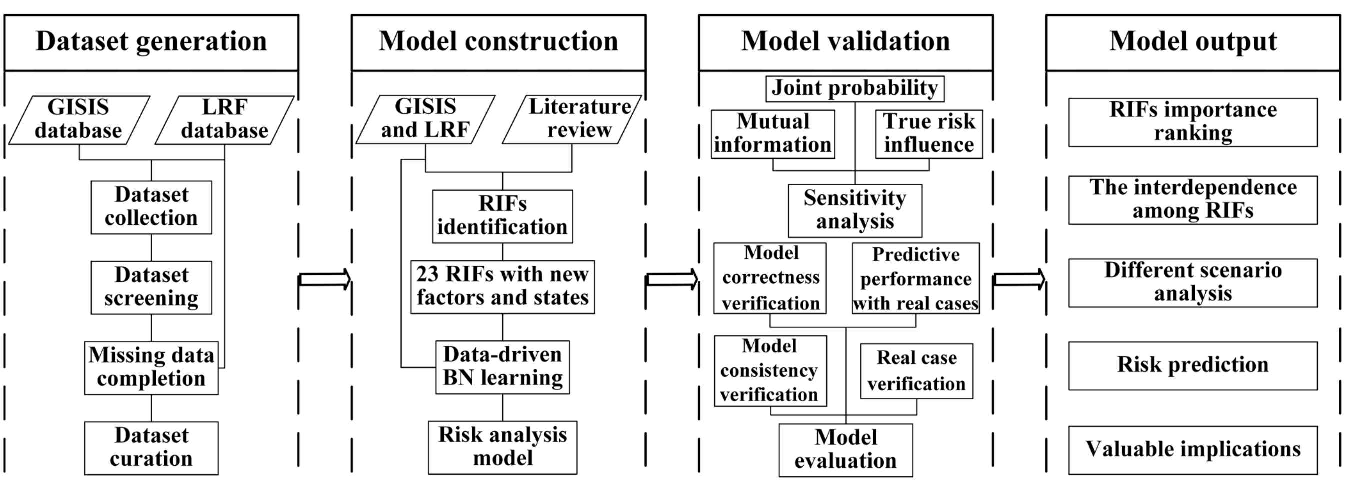

Fig. 2. The proposed methodology.

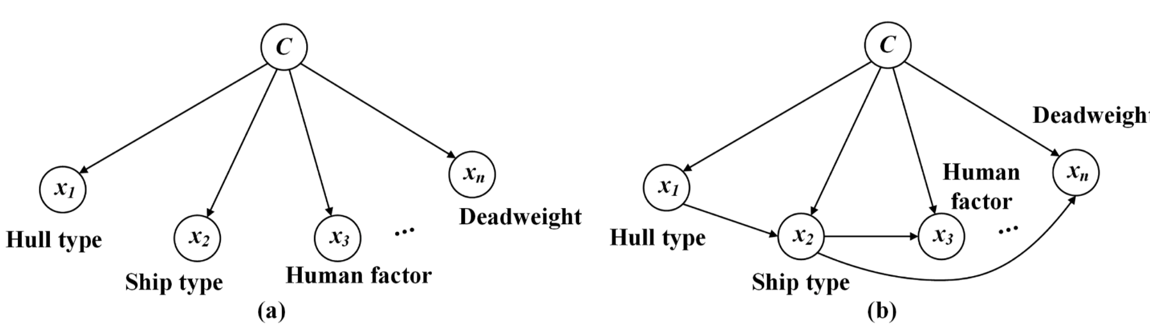

Fig. 3. The structure of an NB network (a) and a TAN network (b).

in step 3; and (4) providing new scenario analysis and drawing insightful implications in step 4.

BN has been proven to be a powerful tool for uncertainty knowledge expression and reasoning [9] and has been widely used in maritime safety fields such as ship accident analysis, decision-making, and risk assessment [33], as described in Section 2. The kernel of a data-driven BN risk model that is constituted by the method for BN structure learning and the sensitivity analysis for implications, will be elaborated in the ensuring sections.

4.1. BN structuring learning

BN structure learning aims to specify the dependencies between variables to build a Directed Acyclic Graph (DAG) mechanism. Data-driven is the process of using machine learning algorithms to learn and construct a BN structure from a dataset. Common data-driven methods include the K2 algorithm, NBN, ABN, and TAN.

The TAN method is an improvement of the NBN method. It deletes the attribute independence assumption of NBN to accommodate the dependencies between attributes. Therefore, TAN not only maintains the robustness of NBN but also makes the network structure more realistic [29]. In the TAN network, each attribute only depends on the class variable and another attribute. The structure of the NBN model and the TAN model is shown in Fig. 3.

TAN learning is essentially an optimisation problem, and its mathematical description is well documented in [24,42,43].

After obtaining the qualitative structure of the TAN network, parameter learning is required to determine the CPT of each node. The commonly used methods for learning parameters from data samples include maximum likelihood estimation and Bayesian estimation for complete data sets, as well as an Expectation-Maximisation algorithm for incomplete data sets [44]. Given that the database constructed in this study is complete, and the Bayesian estimation is more accurate than the maximum likelihood estimation [45], the Bayesian estimation method is selected for parameter learning in this study.

4.2. Sensitivity analysis

Sensitivity analysis is a commonly used uncertainty analysis method. Within the context of BN-based maritime risk analysis, its essence is to identify the RIFs that have a significant impact on the target variable ‘accident type’, so that cost-effective measures with respect to the critical factors can be implemented to reduce the risk [16]. To have a comprehensive evaluation, mutual information, joint probability, and TRI methods are applied to conduct sensitivity analysis from the perspectives of individual and combined variables, respectively. Specifically, the mutual information value can be used to identify the importance and priority of RIF impact on the target node ‘accident type’. It describes the amount of information about another variable obtained through other variables and measures the interdependence between two variables. The larger the mutual information value, the stronger the correlation between the variables. Then additional sensitivity methods (i.e. joint probability and TRI) are applied to explore the detailed effects and interaction of these RIFs. Specifically, the joint probability is used to measure the effect of each state of important RIFs on different types of accidents. TRI is an effective method to test the sensitivity of multiple variables. Furthermore, ordering the RIFs of the 11 accident types based on the TRI value can effectively help obtain the degree of influence of important RIFs on each accident type. Due to their effectiveness, they have been applied in the existing literature in this field individually or jointly [8,19,24,42,46].

4.2.1. Individual variable sensitivity analysis

This study aims to analyze the impact of RIFs on different types of maritime accidents. Therefore, taking ‘accident type’ as a fixed variable, the mutual information value between RIFs and ‘accident type’ is defined as follows:

$$I(C, X_i) = -\sum_{c,i} P(C, X_{ij}) \log_b \frac{P(C, X_{ij})}{P(C)P(X_{ij})} \tag{2}$$

where C is the accident type, X_i indicates the ith RIF, X_{ij} expresses the jth state of the ith RIF, and $I(C, X_i)$ represents the mutual information value between the accident type and the ith RIF. By calculating the mutual information value, it is possible to prioritise the RIFs in an order of their impact on the target node ‘accident type’.

4.2.2. Multiple variables sensitivity analysis

Scenario simulation can explore the impact of these RIFs. The traditional way is to assign different values to the states of the investigation node, and observe the probability change of each state of the target node, when all other nodes are locked [27,33,47]. However, this method is suitable for variables with two states. For variables with multiple states, when the value of one state is modified, it is difficult to determine how other states can change to respond to the modification. Therefore, this study adopted the joint probability and new method (TRI). Joint probability can measure the influence of different RIFs on the target node ‘accident type’ [48]. TRI is put forward by Alyami et al. [49], which is an effective method to test the sensitivity of multiple variables. In this study, the RIFs closely related to the ‘accident type’ are generated from mutual information calculations. When analysing the impact of a chosen RIF, the method raises the probability of its state that has the greatest impact on a certain accident type (e.g. collision) to 100% to get the High Risk Inference (HRI). Then the probability of the state with the least impact on the same accident type is increased to 100% to obtain the Low Risk Inference (LRI). The average of HRI and LRI is calculated to get the TRI of the RIF on collision. The application of a similar process to all other accident types and other RIFs can help obtain the corresponding TRI values. The greater the TRI, the greater the impact of the corresponding RIF on the accident type. Therefore, the effect of the above essential RIFs on the target node ‘accident type’ can be observed in more detail.

4.3. Model evaluation

The proposed data-driven BN risk model needs to be validated before using it for risk diagnosis and/or prediction. This section describes the multiple model validation methods used in this paper. It firstly validates whether the constructed BN model is correct based on two theorems. Then the confusion matrix, overall accuracy, precision, and other indicators are used to evaluate the prediction accuracy and reliability of the model. Finally, the Kappa coefficient is applied to examine the consistency of the model.

4.3.1. Model correctness verification

To test the comprehensive effects of multiple RIFs on ‘accident type’ and verify the correctness of the BN model, the following two theorems must be at least satisfied in the reasoning process of sensitivity analysis [46,50].

Axiom 1. A slight increase or decrease in the prior probabilities of each test node should contribute to the correspondence increase or decrease in the posterior probability of the target node.

Axiom 2. The real influence of the combination of the probability variations of the evidence should be no smaller than the one from a subset of the evidence.

4.3.2. Predictive performance of the model

This study adopts a confusion matrix and several predictive performance evaluation indexes to evaluate the prediction accuracy and reliability of the BN model. A training dataset and a testing dataset are randomly assigned from the new database used in this study. The model is constructed using the training dataset, while the testing dataset is

Table 3
The confusion matrix.

	Actual Positive	Actual Negative
Predicted Positive	True Positive(T_P)	False Positive(F_P)
Predicted Negative	False Negative(F_N)	True Negative(T_N)

utilised for model evaluation.

The overall accuracy is a simple and effective indicator to assess the prediction accuracy of the constructed model, which is defined as the percentage of the total sample that is correctly predicted. However, it is not suitable for measuring results with unbalanced samples. To avoid these problems, precision, recall, F-measure, specificity, and False Positive Rate (*FPR*) are selected to verify the reliability and robustness of the model. Precision is the probability of a positive sample among all predicted positive samples. Recall denotes the probability of being predicted to be positive among actual positive samples, and is also called sensitivity. Precision can evaluate the accuracy of the model, while recall can assess the consistency of the model. Nonetheless, they are mutually restrictive. The F-measure is twice the harmonic mean of precision and recall. The meaning of harmonic mean is to measure the overall average distribution. F-measure should be a balance between precision and recall, and can evaluate the performance of the constructed model more comprehensively. Specificity represents the proportion of all negative samples that are correctly predicted to all actual negative samples. The higher the value of specificity, the better. The smaller the *FPR* value, the better. The confusion matrix is presented in Table 3.

4.3.3. Model consistency verification

In this study, the sample distribution of accident types is uneven, evidenced by the fact that the accident type 'flooding' only accounts for less than 1%. Cohen's Kappa statistic is introduced in this study to verify the model consistency of the prediction performance for each accident type. The calculation of the Kappa statistic is based on the confusion matrix (see Table 3), and the formula is defined as follows:

$$k = \frac{p_o - p_e}{1 - p_e} \tag{3}$$

where k is the Kappa statistic, and p_o indicates the overall accuracy. The calculation p_e is described as follows:

Assuming that the total number of samples in the test dataset is n, the number of real samples of each accident type is $a_1, a_2, \ldots, a_k$ respectively, and the number of each accident type in the prediction result is $b_1, b_2, \ldots$

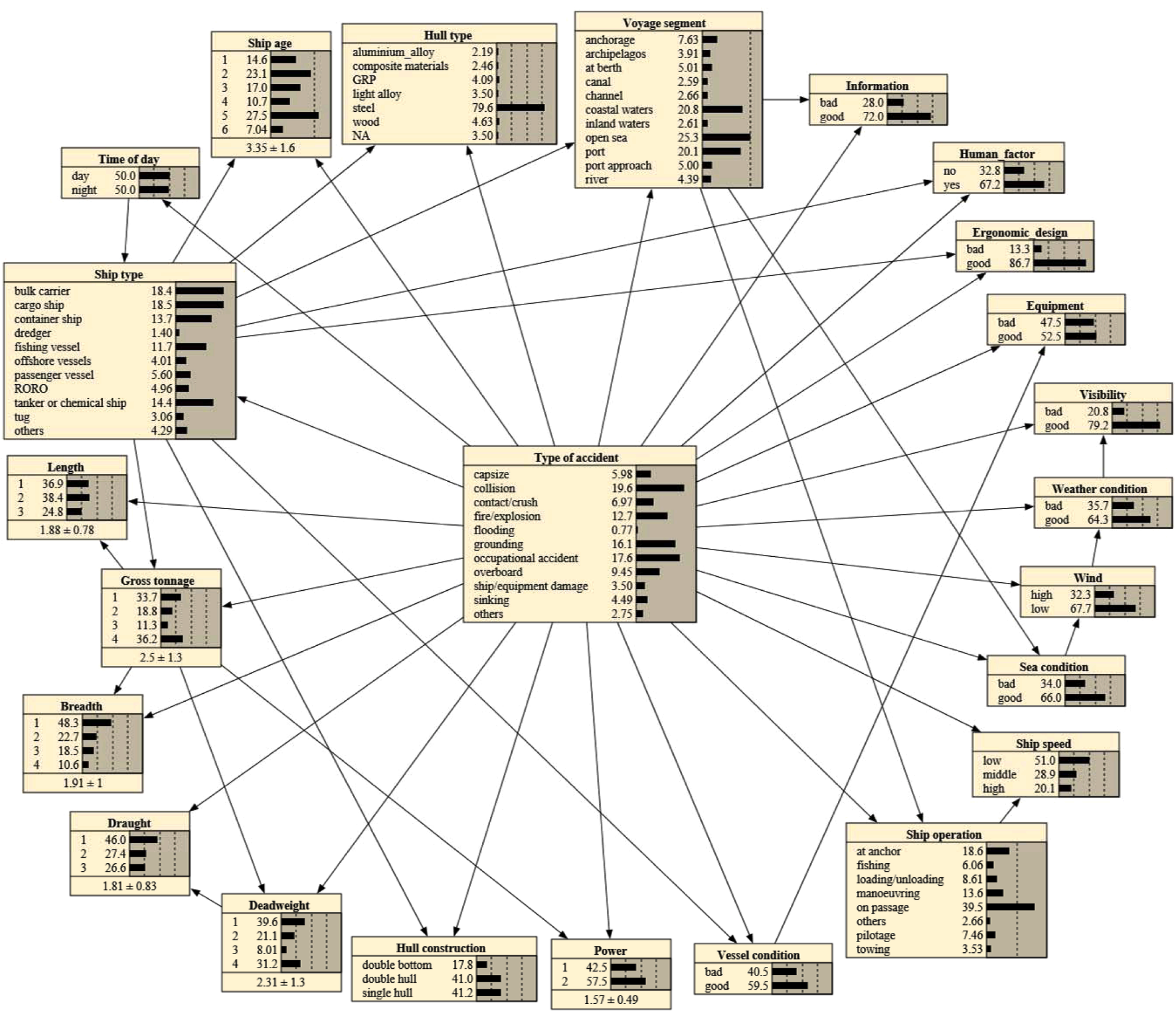

Fig. 4. The final TAN-based BN for the global maritime risk model.

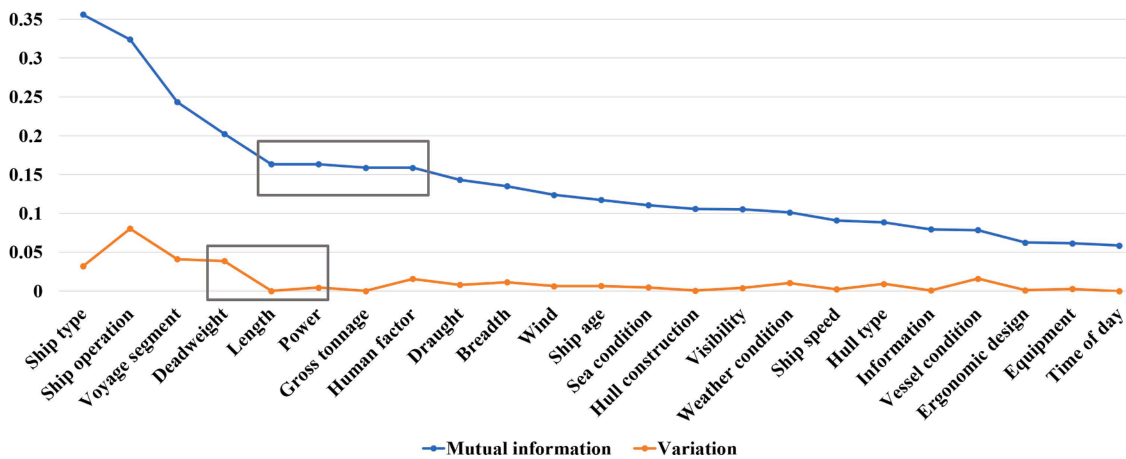

Fig. 5. The visualisation of mutual information value and the variation.

Table 4
Mutual information between 'accident type' and RIFs.

Node	Mutual Information	Entropy Reduction Percent	Variance of Beliefs
Type of accident	3.10454	100	0.754458
Ship type	0.35607	11.5	0.010569
Ship operation	0.324	10.4	0.015278
Voyage segment	0.24345	7.84	0.007116
Deadweight	0.20238	6.52	0.003863
Length	0.16351	5.27	0.002755
Power	0.16333	5.26	0.002567
Gross tonnage	0.15894	5.12	0.002763
Human factor	0.15882	5.12	0.002877
Draught	0.14317	4.61	0.002811
Breadth	0.13508	4.35	0.002691
Wind	0.12375	3.99	0.002735
Ship age	0.11741	3.78	0.003285
Sea condition	0.11074	3.57	0.002579
Hull construction	0.10592	3.41	0.002022
Visibility	0.10536	3.39	0.003895
Weather condition	0.10134	3.26	0.002142
Ship speed	0.09095	2.93	0.002071
Hull type	0.08871	2.86	0.001992
Information	0.07952	2.56	0.004605
Vessel condition	0.07851	2.53	0.00173
Ergonomic design	0.06257	2.02	0.002799
Equipment	0.06143	1.98	0.001286
Time of day	0.05857	1.89	0.002381

, b_k respectively, then the value of p_e is defined as follows:

$$p_e = \frac{a_1 * b_1 + a_2 * b_2 + \cdots + a_k * b_k}{n * n} \tag{4}$$

The calculation result of the Kappa statistic is $k \in [-1,1]$. The closer it is to 1, the stronger the consistency of the model. Scholars [51,52] have demonstrated that the model is almost perfect when $k \in [0.81, 1]$.

4.3.4. Real case analysis

To fully demonstrate the effectiveness of the constructed data-driven BN risk prediction model, a real accident just occurred in 2022 that is not included in the database of 402 records is selected for further verification testing. The real case test can verify the prediction performance and applicability for future accidents.

5. Results, discussion, and implications

5.1. TAN modelling

The conditional mutual information value between each pair of the attribute nodes (i.e. RIFs) is calculated by Eq. (2). Then, the TAN network structure is initially constructed based on the conditional mutual information value of RIFs. The Bayesian estimation method for parameter learning is applied to establish the CPTs of all the nodes with the help of Netica software. The final maritime accident risk BN model is shown in Fig. 4.

It is evident that the posterior probability distribution of the nodes in Fig. 4 provides some initial findings. Collision (19.6%), occupational accident (17.6%), and grounding (16.1%) are the most frequent maritime accident types. From the perspective of ship factors, the ship types involved in the most accidents are cargo ships (18.5%), followed by bulk carriers (18.4%). The length of the ships involved in accidents is most likely between 100 and 200 m (38.4%), and the gross tonnage has 36.2% belonging to 'greater than 20,000 tons'. In addition, 40.5% of the ships involved in accidents are in 'poor condition'.

In terms of the natural environment factors, it is found that 35.7% of the incidents occur in adverse weather conditions and 34% in poor sea conditions. Furthermore, strong wind and low visibility are two important factors, accounting for 32.3% and 20.8%, respectively.

In terms of sailing status, 39.5% of ships involved in accidents are on passage. Most of the accidents occur in coastal waters, accounting for 20.8%, followed by open sea and port with 25.3% and 20.1%, respectively. 28.0% of the ships fail to convey effective information during the voyage, 47.5% are in equipment failures, and 13.3% have ergonomic design problems. Additionally, 67.2% of accidents are related to human factors.

5.2. Sensitivity analysis

5.2.1. Mutual information

The mutual information between the target node 'accident type' and RIFs is calculated. The mutual information value and the corresponding variation are shown in Fig. 5. The corresponding variation presents the difference between two adjacent mutual information. The greater the mutual information value, the more significant the impact of the corresponding RIF on the 'accident type'. Furthermore, the mutual information value, entropy reduction percentage, and variance of beliefs are listed in Table 4. It can be seen that 'ship type' has the greatest impact on 'accident type', with a mutual information value of 0.35607, followed by 'ship operation' and 'voyage segment' with 0.324 and 0.24345, respectively.

Table 5
The joint probability (100%).

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
Initial	5.98	19.62	6.97	12.68	0.77	16.15	17.64	9.45	3.50	4.49	2.75
Ship type											
bulk carrier	**0.25**	29.16	1.52	8.04	**0.16**	14.61	**30.46**	9.24	3.75	1.45	1.37
cargo ship	3.97	17.30	11.51	4.15	**2.60**	21.09	22.39	7.89	1.40	7.47	**0.23**
container ship	2.02	16.24	5.34	15.98	0.21	14.36	26.69	8.93	3.47	**0.32**	6.44
dredger	**35.49**	3.45	3.31	3.41	2.07	**3.44**	20.25	3.37	3.10	**19.12**	2.99
fishing vessel	21.91	12.76	2.38	18.64	0.25	10.67	2.48	22.39	**0.37**	6.06	2.11
offshore vessels	1.14	**1.20**	12.65	13.06	0.72	**43.26**	**1.19**	7.08	6.46	12.20	1.04
passenger vessel	4.83	13.74	**33.86**	5.13	0.52	18.06	5.05	**0.84**	**8.49**	8.74	0.74
RORO	0.92	10.68	14.91	**44.02**	0.58	10.65	5.86	0.95	5.22	5.37	0.84
tanker	0.32	28.88	1.94	16.95	0.20	10.33	18.84	6.90	6.30	1.85	**7.50**
tug	16.35	17.30	1.50	17.09	0.94	9.44	1.56	**24.34**	1.41	8.71	1.36
others	22.18	**29.38**	**1.08**	**1.11**	0.67	29.25	6.79	6.53	1.01	1.04	0.97
Ship operation											
at anchor	**2.06**	**2.56**	7.38	11.35	0.81	23.91	21.02	**19.84**	3.38	4.52	3.18
fishing	**34.38**	4.15	3.46	**18.08**	1.05	7.65	3.94	16.92	2.74	3.09	4.54
loading/unloading	4.15	5.54	2.43	16.93	0.74	**2.90**	**55.69**	**2.55**	5.37	2.17	1.52
manoeuvring	5.63	**35.86**	19.73	4.81	**0.47**	20.91	3.30	4.63	2.33	**1.38**	**0.96**
on passage	2.88	29.60	**1.47**	16.30	0.60	11.55	19.08	6.12	3.61	6.04	2.75
others	13.43	9.44	7.87	9.05	**2.40**	9.37	8.96	16.01	**6.24**	**12.30**	**4.92**
pilotage	4.98	12.20	**20.08**	**3.23**	0.86	**38.57**	**3.20**	8.43	**2.23**	2.51	3.72
towing	14.76	19.51	5.94	12.47	1.81	13.13	6.76	11.89	4.71	5.30	3.71
Voyage segment											
anchorage	**1.74**	11.26	4.67	10.60	0.50	26.22	20.17	15.73	**1.55**	6.44	**1.12**
archipelagos	7.52	15.71	13.69	4.67	0.97	31.26	4.31	13.08	3.02	3.58	2.18
at berth	2.65	**3.88**	11.32	20.09	0.76	**4.10**	**39.96**	6.84	5.91	2.79	1.70
canal	5.12	25.01	**18.84**	7.06	1.47	16.52	6.51	6.21	4.56	5.41	3.30
channel	4.98	7.30	5.51	6.86	1.43	**39.91**	15.07	6.04	4.44	5.26	3.21
coastal waters	12.66	32.13	2.49	10.84	**0.18**	19.31	**1.90**	9.39	3.48	4.98	2.63
inland waters	**13.21**	7.44	13.66	6.99	1.45	7.85	6.45	**29.79**	4.52	5.36	3.27
open sea	2.91	21.99	**2.06**	**21.13**	0.61	4.24	28.76	6.38	3.11	4.97	**3.83**
port	3.97	10.38	11.85	9.72	0.77	20.27	25.83	8.95	3.54	**1.96**	2.76
port approach	10.10	**34.60**	11.30	**3.65**	**3.10**	20.33	3.37	**3.21**	2.36	6.27	1.71
river	3.01	19.42	12.18	9.08	0.86	19.17	3.83	17.55	**6.17**	**29.79**	1.94
Deadweight											
1	**12.83**	14.27	**10.86**	**10.55**	**1.34**	**23.79**	**3.92**	10.88	**2.03**	**8.08**	1.45
2	1.77	24.90	4.90	**17.85**	0.38	13.32	22.51	**5.23**	**4.72**	3.98	**0.43**
3	4.68	**7.72**	10.31	13.46	1.00	16.80	28.83	7.76	4.20	1.23	4.00
4	**0.45**	**25.90**	**2.58**	11.67	**0.26**	**8.19**	**28.90**	**10.93**	4.36	**1.11**	**5.67**
Length											
1	**13.98**	**14.72**	**9.79**	**10.06**	**1.53**	**23.69**	**4.28**	**11.79**	**1.03**	**8.18**	**0.94**
2	1.70	20.92	6.01	13.83	**0.27**	13.27	25.22	8.08	**5.09**	2.90	2.74
3	**0.70**	**24.91**	**4.27**	**14.78**	0.41	**9.40**	**25.77**	**8.10**	4.71	**1.46**	**5.47**
Power											
1	**13.51**	**16.90**	**10.36**	**11.11**	**1.47**	**21.81**	**5.52**	**10.35**	**0.96**	**7.14**	**0.88**
2	**0.42**	**21.63**	**4.47**	**13.83**	**0.25**	**11.97**	**26.60**	**8.79**	**5.37**	**2.53**	**4.14**

Table 6
TRI of RIFs for all accident types.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	Average
Ship type	17.62	14.09	16.39	21.46	1.22	19.91	14.64	11.75	4.06	9.40	3.64	11.66
Ship operation	16.16	16.65	9.31	7.42	0.96	17.83	26.24	8.64	2.01	5.46	1.98	10.24
Voyage segment	5.74	15.36	8.39	8.74	1.46	17.91	19.03	13.29	2.31	13.91	1.36	9.77
Deadweight	6.19	9.09	4.14	3.65	0.54	7.80	12.49	2.85	1.34	3.49	2.62	4.93
Length	6.64	5.09	2.76	2.36	0.63	7.14	10.75	1.86	2.03	3.36	2.27	4.08
Power	6.54	2.37	2.95	1.36	0.61	4.92	10.54	0.78	2.21	2.30	1.63	3.29

The blue line is the result of the mutual information value, while the orange line indicates the variation between the two adjacent mutual information values in Fig. 5. It is evident that the 6th, 7th, and 8th mutual information values do not change much from the comparison of the two grey boxes. Furthermore, the variation of the 6th and 7th, 7th and 8th, and 8th and 9th mutual information values is 0.00018, 0.00439, and 0.00012, respectively. According to the mutual information value and the rate of change, the first six RIFs are the factors with the greatest influence and the most obvious rate of change. Therefore, in the model correctness verification, the first six important risk identification factors are selected as the judgement criteria to verify the correctness of the model based on the TRI value, as listed below.

Ship type > Ship operation > Voyage segment > Deadweight > Length > Power

It is proved that 'deadweight' and 'hull construction' have significant effects on 'accident type' by calculating the mutual information, which also illustrates the correctness of introducing 'deadweight' and 'hull construction' as RIFs in global maritime accident risk analysis.

5.2.2. Joint probability

For the most important variables screened from mutual information calculations, additional sensitivity methods are used to explore the

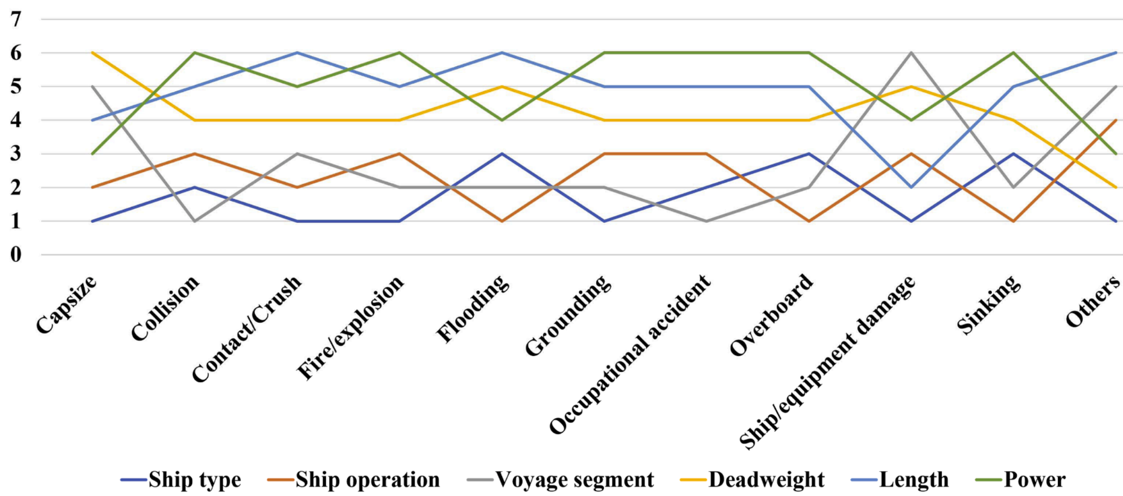

Fig. 6. The top six important RIFs for all accident types.

Table 7
The result of minor changes in RIFs.

Power		+2%	+2%	+2%	+2%	+2%	+2%
Length			+2%	+2%	+2%	+2%	+2%
Deadweight				+2%	+2%	+2%	+2%
Voyage segment					+2%	+2%	+2%
Ship operation						+2%	+2%
Ship type							+2%
S1	5.98	6.24	6.51	6.76	7.01	7.73	8.47
S2	19.62	19.72	19.92	20.29	20.94	21.48	22.20
S3	6.97	7.09	7.20	7.36	7.70	8.44	8.89
S4	12.68	12.73	12.83	12.98	13.33	14.25	14.61
S5	0.77	0.79	0.82	0.84	0.90	0.96	1.01
S6	16.15	16.35	16.63	16.94	17.66	18.09	18.91
S7	17.64	18.06	18.49	18.99	19.79	20.40	21.51
S8	9.45	9.48	9.56	9.67	10.20	10.67	11.04
S9	3.50	3.59	3.67	3.72	3.82	4.00	4.09
S10	4.49	4.58	4.72	4.85	4.95	5.32	5.58
S11	2.75	2.82	2.91	3.01	3.07	3.23	3.32

detailed effects of these RIFs on 'accident type'. The probability of each state of each variable is sequentially increased to 100% to obtain the joint probabilities [9], as shown in Table 5. For clear illustration, the states of 'accident type' (i.e. capsize, collision, contact/crush, fire/explosion, flooding, grounding, occupational accident, overboard, ship/equipment damage, sinking, and others) are sequentially expressed as S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, and S11 in this section.

Table 10
The details of one real accident in 2022.

RIFs	State	RIFs	State	RIFs	State
Ship type	Bulk carrier	Power	1192	Ship operation	On passage
Hull type	Steel	**Hull construction**	**NA**	Voyage segment	Inland waters
Ship age	10	Vessel condition	Good	Speed	9.3
Length	98	Time of day	Night	Equipment	Good
Breadth	19.8	Wind	Low	Ergonomic design	Good
Gross tonnage	3807	Visibility	Good	Information	Bad
Deadweight	**NA**	Weather condition	Good	Human factor	Yes
Draught	**NA**	Sea condition	Good		

Table 8
Confusion matrix of the predicted results.

Predicted	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	Actual total	Accuracy rate (%)
S1	5	0	0	0	0	0	0	0	0	0	0	5	100
S2	0	15	0	0	0	0	1	0	0	0	0	16	93.75
S3	0	0	4	0	0	0	1	0	0	0	0	5	80
S4	0	0	0	8	0	0	2	0	0	0	0	10	80
S5	0	0	0	0	2	0	0	0	0	0	0	2	100
S6	0	0	0	0	0	10	0	1	1	0	0	12	83.33
S7	0	0	0	0	0	0	14	0	0	0	0	14	100
S8	0	0	0	0	0	0	0	7	0	1	0	8	87.5
S9	0	0	0	0	0	0	1	0	2	0	0	3	66.67
S10	0	0	0	0	0	0	0	0	0	3	0	3	100
S11	0	0	0	0	0	0	0	0	0	0	2	2	100
Total	5	15	4	8	2	10	19	8	3	4	2	80	90

Table 9
Performance results for each accident type.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
Precision	1	1	1	1	1	1	0.737	0.875	0.667	0.75	1
Recall	1	0.938	0.8	0.8	1	0.833	1	0.875	0.667	1	1
F-measure	1	0.968	0.889	0.889	1	0.909	0.848	0.875	0.667	0.857	1
Specificity	1	0.987	0.987	0.972	1	0.971	1	0.987	0.987	1	1
FPR	0	0.013	0.013	0.028	0	0.029	0	0.013	0.013	0	0

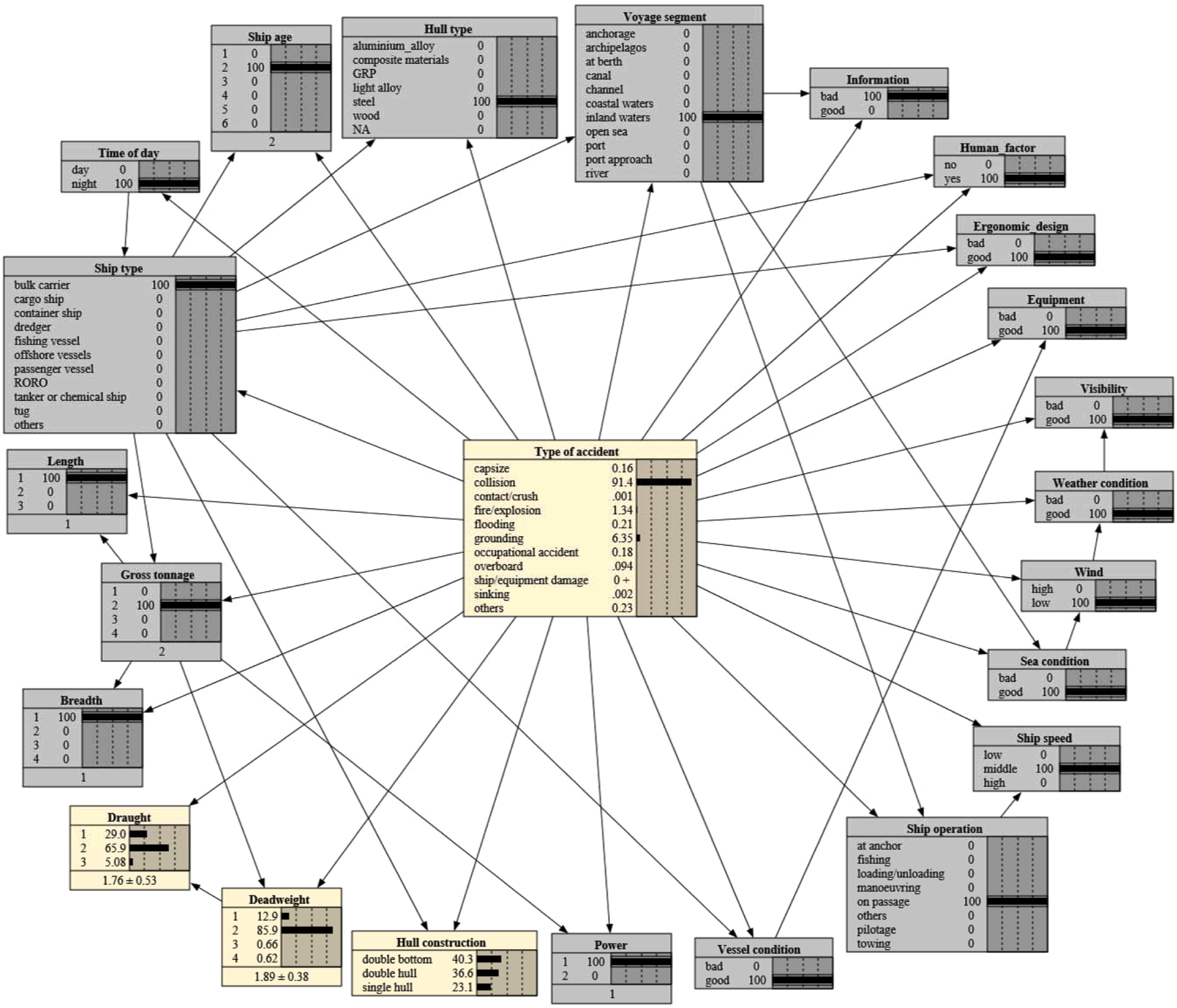

Fig. 7. Real case verification.

The results of each state in different variables on accident types are displayed in Table 5. A comparison with the raw probabilities in the initial row of Table 5 shows how the probability of each accident type changes when a chosen RIF is set in a particular state. In particular, it shows the states where each variable has the greatest and least impact (in bold value) on different accident types.

Therefore, new findings are revealed for useful insights. For example, the probability of capsizing is the largest when the ship is fishing and the smallest when the ship is at anchor. For passenger ships, it is most likely to be engaged in an overboard accident and the least likely to have a contact accident. When ships are larger, manoeuvring or sailing in waters close to ports, the probability of collision accidents is greatly increased.

5.2.3. True risk influence

Based on the original probability and bold values in Table 5, the TRI value of the top six critical RIFs for the target node 'accident type' can be calculated. Taking the calculation of the TRI value of 'ship operation' to 'collision' (S3) as an example, it is found that according to the probability value of 'collision' in the second column of Table 5 'manoeuvring' is the state that has the greatest impact on 'collision'. At this time, the probability of 'collision' is 35.86 (100%), and the difference between 35.86 and the original probability value of 19.62 is HRI (i.e. 16.24). While 'at anchor' is the state with the least impact on 'collision' with the probability of 2.56, the difference between 2.56 and the original probability value is LRI (i.e. 17.06). Then the average of HRI and LRI is calculated as 16.65 to get the TRI value of 'ship operation' to 'collision'. The same process is applied to other RIFs and accident types to calculate the TRI values of all the RIFs for each accident type, as shown in Table 6.

It is clear that the influence of the RIFs on maritime accident risk varies with different accident types. According to the TRI values, the importance of RIFs for 11 accident types is sorted from 1 (i.e. the most important) to 6 (the least important), as displayed in Fig. 6. It is evident that 'ship operation' has a greater impact on 'flooding', 'overboard', and 'sinking' than on other types of accidents. 'Voyage segment' is the most important RIF for 'collision' but the least important RIF for 'Ship/ equipment damage'.

5.3. Model evaluation

5.3.1. Model correctness verification

To verify the model correctness, another sensitivity analysis is performed to test the comprehensive effects of multiple variables. When taking take the top six important RIFs as a set of variables, we make

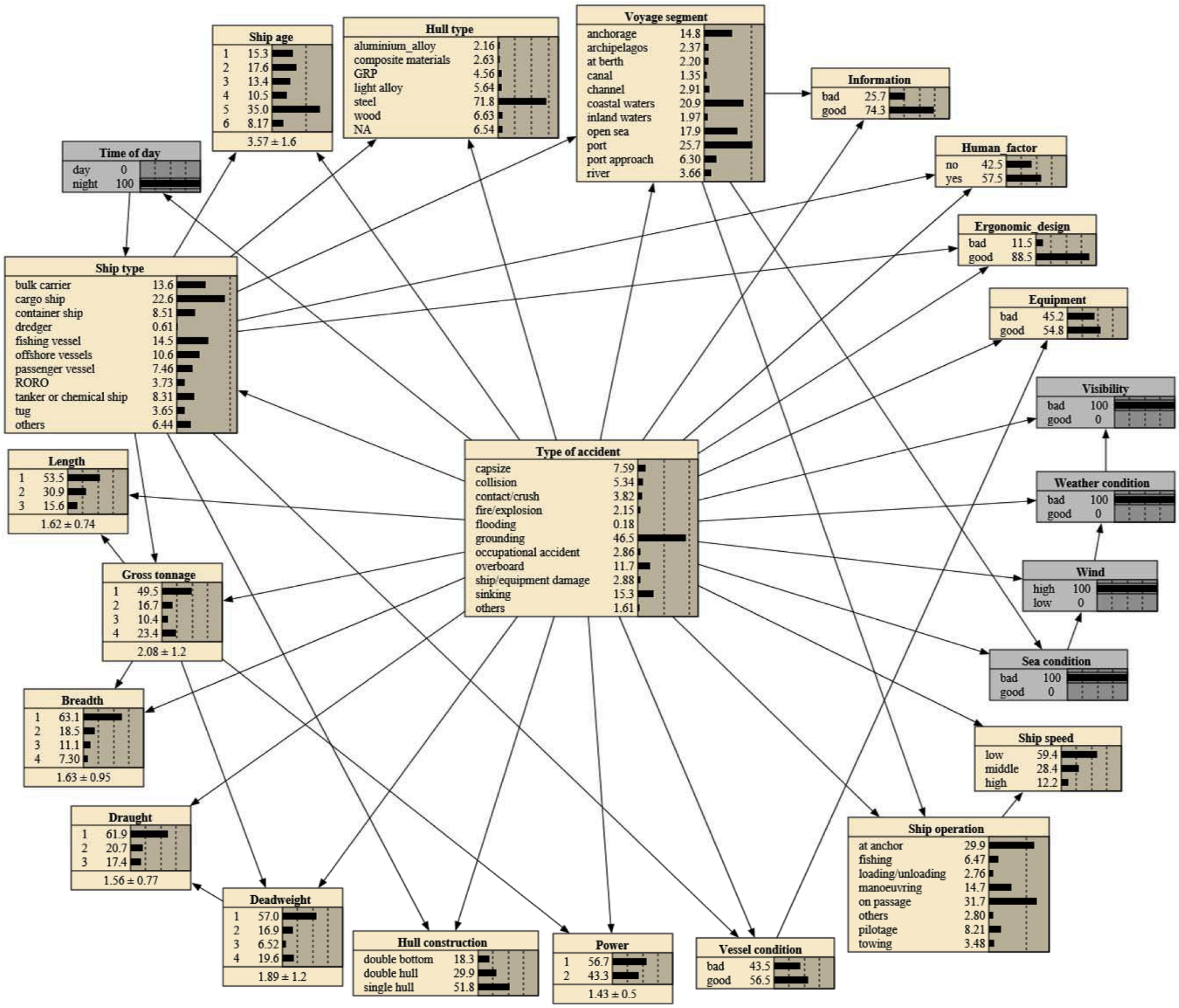

Fig. 8. Scenario for adverse environmental conditions.

small changes in the prior probability of these variables, and observe the probability changes of the target node ‘accident type’. The change value is set as an increase of ‘2%’. The probability of a chosen node is increased by 2% towards its two extreme states that hava the most and least impact on ‘collision’, respectively. Then this process is repeated from the first to the last investigated nodes. As a result, the updated cumulative change values in the order of power, length, deadweight, voyage segment, ship operation, and ship type are obtained. Similarly, the above procedure is applied to other accident types, and the results are calculated and listed in Table 7. The first column in Table 7 shows the original probability value of each accident type, and the remaining columns express the updated cumulative change values of the result. The combined effects of these important RIFs on the ‘accident type’ can be calculated by comparing changes in probability values.

According to Tables 6 and 7, the increase or decrease of the prior probability of the variable node will lead to the increase or decrease of the posterior probability of the target node, which tests Axiom 1. From Table 7, the probability value of the target node gradually increases with the continuous updating of the change of the investigated RIFs, and therefore Axiom 2 is tested. The proposed model in this study conforms to Axiom 1 and Axiom 2, verifying its correctness.

5.3.2. *Predictive performance of the model*

For testing the prediction performance, 80 accident records (20%) are randomly selected, reserved, and used as the testing datasets. The test results are displayed in a confusion matrix, as shown in Table 8. The overall accuracy of the model calculated from the confusion matrix is 90% (72/80). According to the accuracy rate in Table 8, it is evident that the prediction accuracy rates are 100% in S1 (capsize), S5 (flooding), S7 (occupational accident), S10 (sinking), and S11 (others). The accuracy rates of S2 (collision), S6 (grounding), and S8 (overboard) are 93.75%, 83.33%, and 87.5%, respectively.

According to Section 4.3.2, five prediction performance indicators of each accident type are calculated, as shown in Table 10. The precision of the proposed BN model is captured to be 100% in S1 (capsize), S2 (collision), S3(contact/crush), S4 (fire/explosion), S5 (flooding), S6 (grounding), and S11 (others). The recall of the model is calculated to be 100% in S1 (capsize), S5 (flooding), S10 (sinking), and S11 (others). It is apparent that the F-measure values of the constructed model are higher than 0.8. The higher the value of specificity, the better. The smaller the *FPR* value, the better. From Table 9, the specificity values of all accident types are more than 97%, while the *FPR* values are less than 3%. The comparison results of five prediction indexes further demonstrate the excellent performance and reliability of the constructed model.

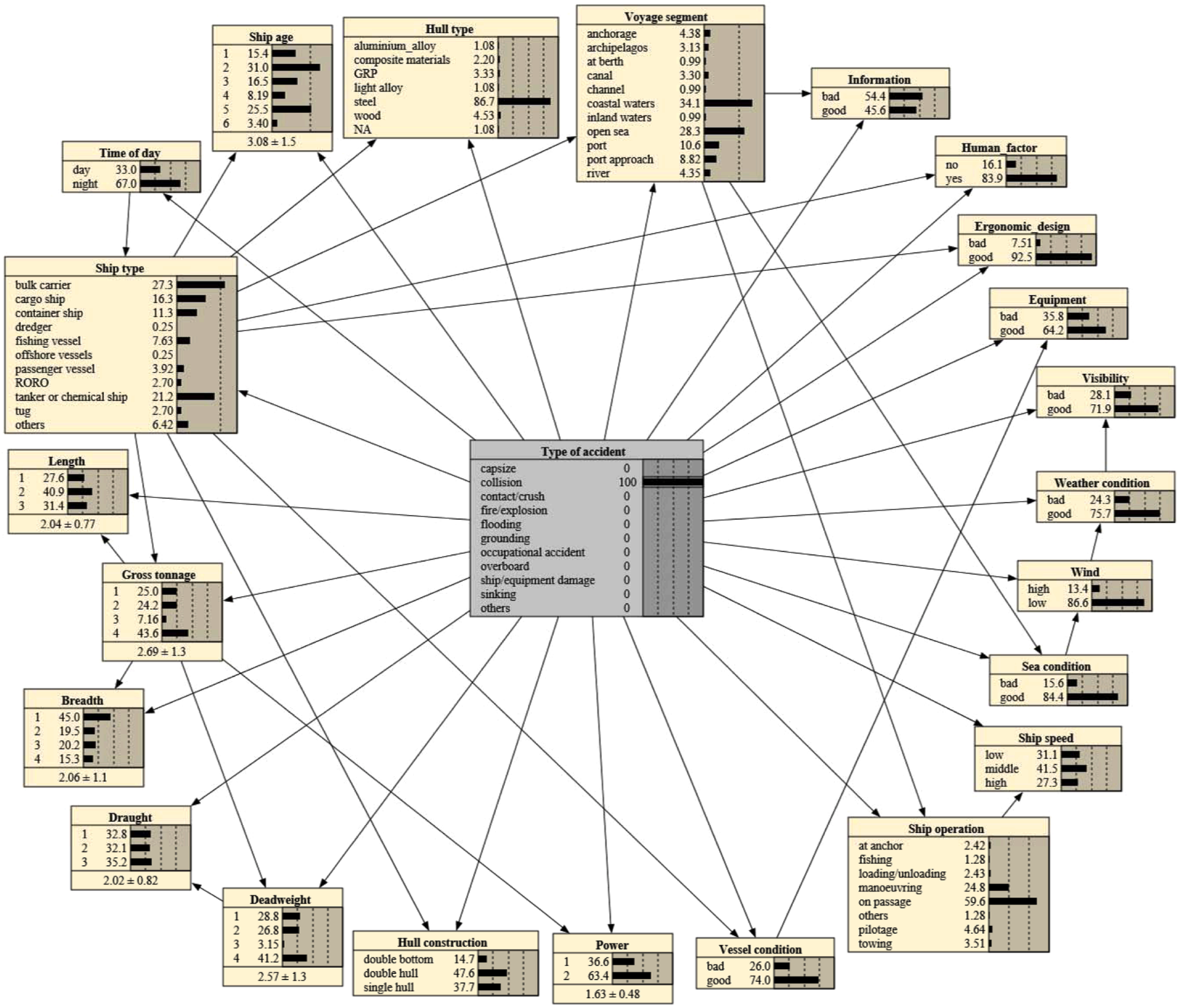

Fig. 9. Scenario for collision.

5.3.3. *Model consistency verification*

According to Eq. (4) and the confusion matrix (see Table 9), $p_e = 0.132$ can be calculated. The value of p_o is the overall accuracy rate, i.e. 0.9. According to Eq. (13), the Kappa coefficient is calculated to be 0.8848. It is well known that the model is almost perfect when $k \in [0.81, 1]$. The verification further indicates that the constructed model has strong consistency.

5.3.4. *Real case verification*

To further demonstrate the validity of the model, a marine accident that just occurred in 2022 (excluded from the database of 402 records) is selected for testing. On 4th Jan. 2022, the bulk carrier 'Tian XXXX8′ collided with a fishing vessel in an inland waterway in China. According to the accident report record, the parameters of 23 RIFs are shown in Table 10. The information on deadweight, draught, and ship construction is missing from the accident records and hence treated as 'unknown – without any locked evidence in Fig. 7'. The accident is simulated with the constructed BN risk prediction model, as shown in Fig. 7. Despite the three unknown nodes, it is clear that the probability of ship collision is as high as 91.4%. The real case verification further demonstrates the effectiveness of the constructed BN model in this paper. It can be used with confidence in a proactive way to avoid the reoccurrence of a similar accident in future when a high probability is calculated and observed proactively.

5.4. *Scenario analysis*

Scenario analysis explores the impact of specific conditions on various accident types by modifying the states of nodes. Through the analysis of some concerning scenarios, the risk of different accidents, specific scenarios, and the combination of multiple RIFs can be revealed, thereby effectively assisting maritime authorities in formulating rational and effective accident prevention countermeasures.

5.4.1. *Scenario one: adverse environmental conditions*

Scenario one simulates the occurrence likelihood of various accidents under adverse environmental conditions. In this situation, the setting is given as 'time of day' as night, 'wind' as high, 'visibility' as bad, 'weather condition' as bad, and 'sea condition' as bad. As shown in Fig. 8, the risk probability of 'grounding' and 'sinking' increase significantly, especially the result of 'grounding' changes from 16.1 to 46.5%. This finding shows that when the natural environment is unfavourable, grounding and sinking accidents are more likely to occur. Weather routing is important in maritime safety. It provides a valuable

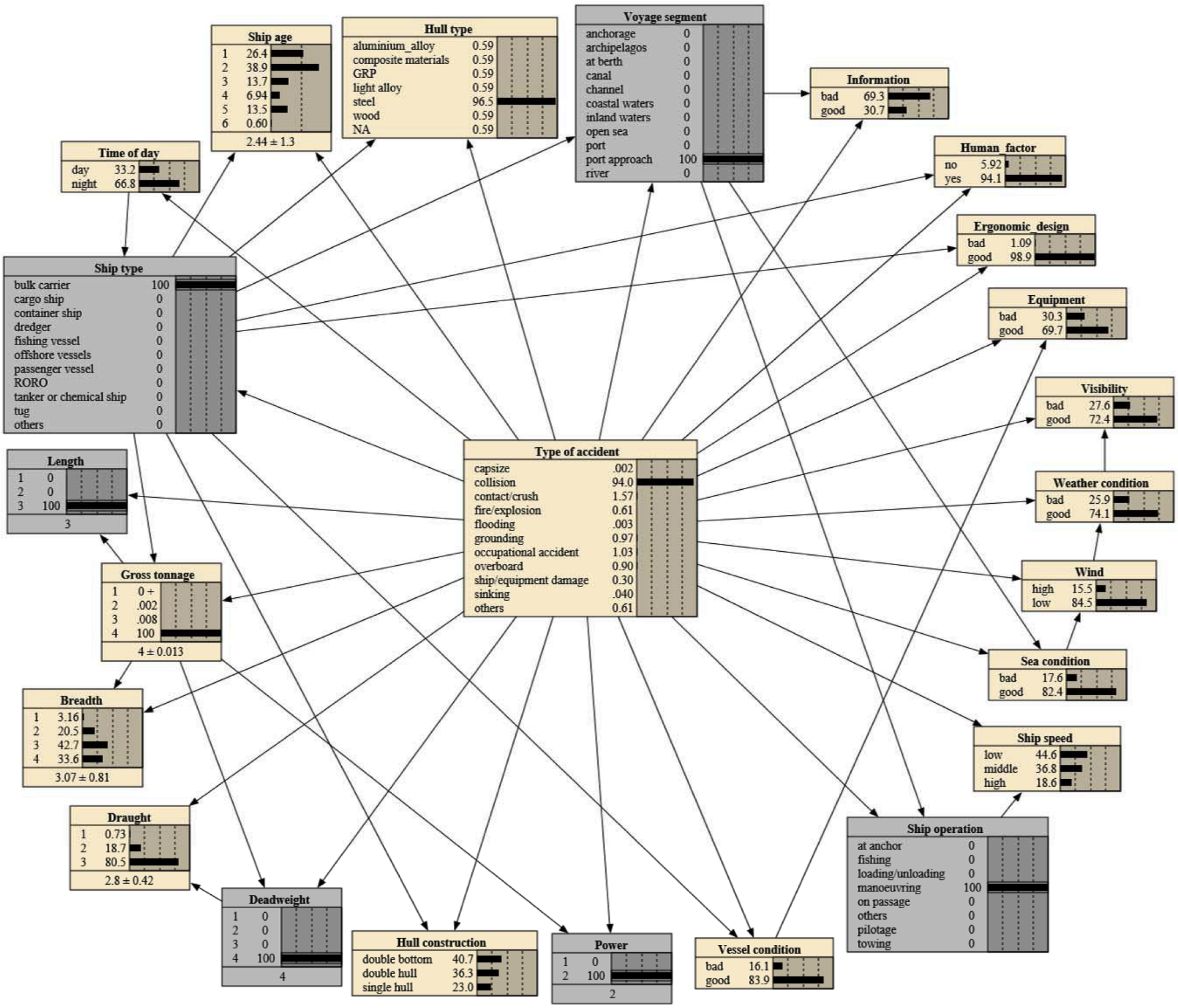

Fig. 10. The most likely scenario for collision.

implication for transportation authorities and shipowners to pay more attention to grounding and sinking accidents in a bad navigation environment. Meantime, the decision-makers should formulate some regulations for navigating under bad weather. Furthermore, the shipbuilders should also improve the stability during the design process.

5.4.2. Scenario two: the most likely scenario for collision

When the state of 'collision' is set as 100%, it can reveal the most likely scenario of a collision accident. The scenario results are shown in Fig. 9. The probabilities of a few nodes significantly increased, including the bulk carrier or tanker in 'ship type', on passage and manoeuvring in 'ship operation', coastal waters and open sea in voyage segment and at night in 'time of day'. It uncovers that collision accidents are likely to occur in the situation composed of the above node states. These findings provide useful insights for relevant authorities that when bulk carriers or tankers navigate or manoeuvre in coastal waters at night, ship collision risk is very high. Effectively traffic control such as better traffic lanes and only day-time operation for high-risk coastal areas should be implemented.

5.4.3. Scenario three: the combined impact of important RIFs

Scenario analysis can explore the combined impact of the top six important RIFs (i.e. ship type, ship operation, voyage segment, deadweight, length, and power) on the target node 'accident type'. For instance, each RIF is assigned a 100% probability to the state that generates the highest joint probability with 'collision' to demonstrate the riskiest scenario of 'collision'. As shown in Fig. 10, the probability of 'collision' significantly increases from 19.62 to 94%. This finding indicates that there is an extremely high risk of collision when large bulk carriers are manoeuvring in the port approach area. Therefore, relevant departments should take measures against these critical factors to avoid ship collision, such as improving the manoeuvrability of bulk carriers, strengthening the monitoring and lookout when entering or leaving a port, and ensuring the correct operation of the crew when manoeuvring the ship.

Similarity, the most likely scenario for 'grounding' is displayed in Fig. 11, with the probability increasing from 16.15 to 96.8%. It indicates that the probability of grounding is exceptionally high when small offshore ships pass through a strait under pilotage. Due to the harsh traffic conditions in the strait and possible pilot errors, ship groundings still occur frequently. This finding provides valuable implications for different maritime stakeholders to take regulations and reduce the grounding risk. Maritime authorities should strengthen traffic management in a strait. Ships should choose the correct routes when passing

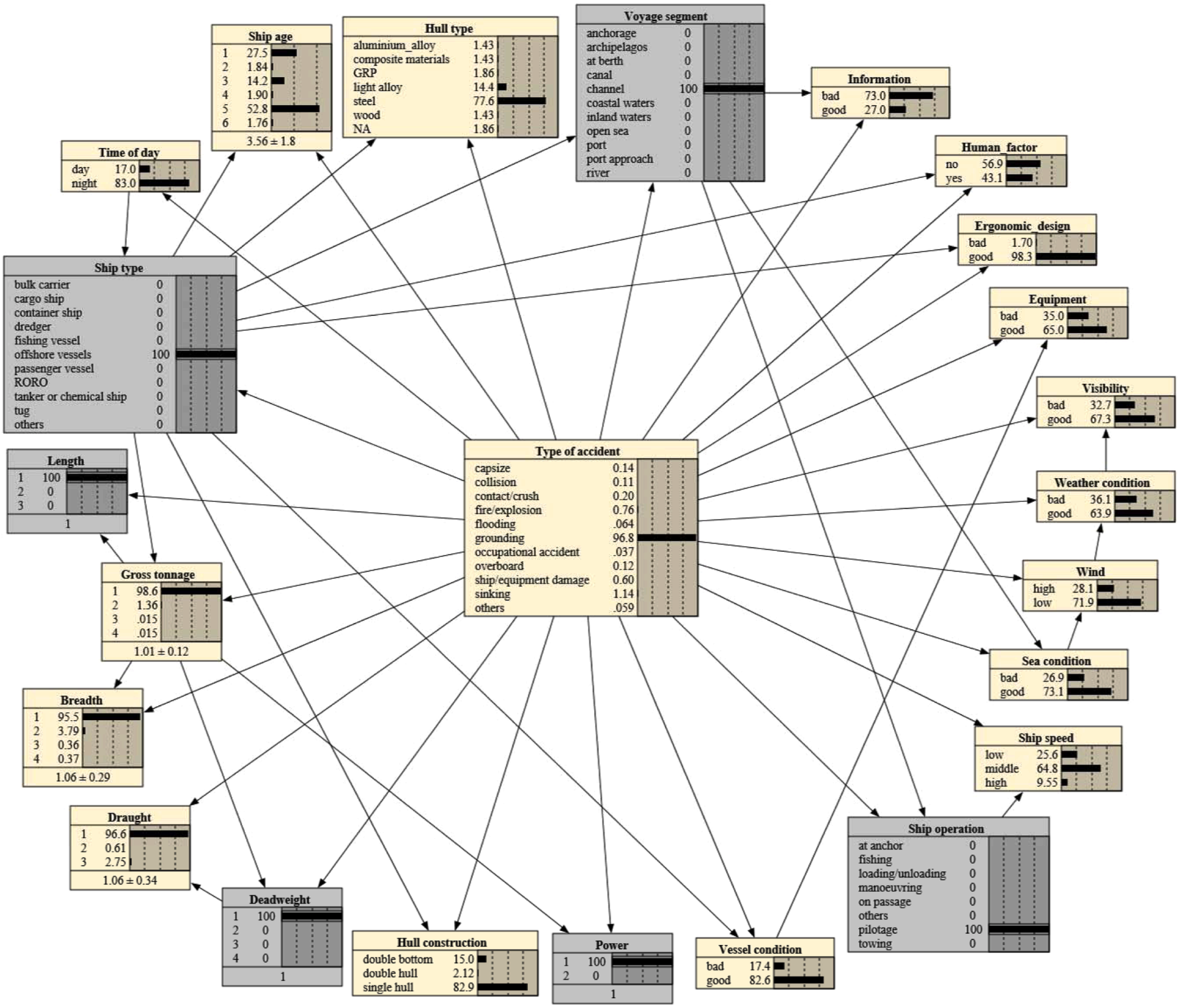

Fig. 11. The most likely scenario for grounding.

through a channel and be equipped with advanced navigation equipment and electronic charts to assist navigation. In addition, pilots should also improve their operational level and safety awareness.

5.5. Implications

From the perspective of ship types, it reveals that tankers have the highest risk on collision, RORO on fire/explosion, cargo ships on grounding, and fishing vessels on capsizing and overboard. Furthermore, small ships are more likely to have grounding accidents, while larger ships are more prone to collisions and occupational accidents.

Regarding ship operation, the highest risk for capsizing is in fishing operation, occupational accidents in loading/unloading, collision is on passage, and grounding in pilotage.

As far as the voyage segment is concerned, collision accidents mostly likely occur in coastal waters and port approach, occupational in port, and grounding in a channel.

The top six important RIFs are ship type, ship operation, voyage segment, deadweight, length, and power. Accordingly, decision-makers in maritime stakeholders can gain valuable insights on how to prevent maritime accidents, plan routes, prioritise emergency optimisation resources, and reduce risk. Besides, the accident types in different voyage segments vary, indicating maritime authorities should enhance cooperation with other stakeholders to formulate safety policies and regulations for maritime transportation, especially for collision, occupational accidents, grounding, and fire/explosion.

Based on the complete and incomplete information listed in the 23 RIFs, different stakeholders can apply this risk prediction model to make optimal decisions to prevent accidents. The insurance companies can evaluate the quota and make various pricing strategies for different shipowners. Simultaneously, maritime authorities can provide an early warning based on scenario analysis results.

Especially, hull construction is the first time introduced to explore its influence on maritime accidents. The detailed states (i.e. double hull, single hull, and double bottom) of the hull construction can provide useful insights for shipbuilders to consider the comprehensive performance of ships. As a result, the findings become insightful for the development of safety for design in the shipbuilding market.

Furthermore, the real case verification also demonstrates the prediction accuracy is up to 91.4%. This study leads to the advanced risk prediction model for preventing accidents.

Finally, the scenario analysis of collision and grounding provides useful suggestions for bulk carriers, tanker ships, and offshore vessels to take effective measures when navigating specific segments.

6. Conclusion

This paper uses a data-driven BN network to construct a risk analysis model to quantify the impact of 23 RIFs on different maritime accident types. To solve the problems of insufficient and outdated risk data, a new database with comprehensive records against all the IMO regulated RIFs is built by using the GSIS and LRF databases in the past five years. Referring to the literature review and the IMO guidance materials, 23 RIFs are identified to construct the BN-based risk model. Sensitivity analysis and different scenario simulations are carried out to identify the most important influential factors, investigate their combined effects and reveal the risk in different situations.

The findings in this paper provide valuable implications for maritime accident prevention.

(1) The top six influential RIFs for maritime accidents are ship type, ship operation, voyage segment, deadweight, length, and power.
(2) This study uncovers the combined influence of different RIFs and explores the combined effects of their different states, enabling the simulation results of different scenarios against real cases.
(3) This study improves the methodology of developing a data-driven BN risk model and can predict maritime accident risk accurately. The real case prediction accuracy is 91.4%, and hence the model can be used for accident prevention.
(4) It is apparent that the three scenario analysis revealed critical information about ship type and navigation conditions in collision and grounding. Meantime, the typical accident features are mined for different stakeholders to make economic transportation plans and trajectories.

CRediT authorship contribution statement

Huanhuan Li: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xujie Ren:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Zaili Yang:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zaili Yang reports financial support was provided by European Research Council. The authors declare no conflict of interest.

Data availability

The data that has been used is confidential.

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