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Analysis of maritime transport accidents using Bayesian Networks

Shiqi Fan[1,2,4], Zaili Yang[4], Eduardo Blanco-Davis[4], Jinfen Zhang[2,3], Xinping Yan[1,2,3*]

[1]School of Energy and Power Engineering, Wuhan University of Technology, China
[2]Intelligent Transport Systems Research Centre (ITSC), Wuhan University of Technology, China
[3] National Engineering Research Centre for Water Transport Safety (WTSC), MOST, Wuhan, China
[4] Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK

*Corresponding Author e-mail: xpyan@whut.edu.cn (X. Yan)

*Permanent Address: Y125 mailbox, Yujiatou Campus, Wuhan University of Technology, 1178 Heping Avenue, Wuchang District, Wuhan City, P. R. China, 430063

Abstract: A Bayesian Network-based risk analysis approach is proposed to analyse the risk factors influencing maritime transport accidents. Comparing with previous studies in the relevant literature, it reveals new features including 1) new primary data directly derived from maritime accident records by two major databanks Marine Accident Investigation Branch (MAIB) and Transportation Safety Board of Canada (TSB) from 2012 to 2017, 2) rational classification of the factors with respect to each of major types of maritime accidents for effective prevention, and 3) quantification of the extent to which different combinations of the factors influence each accident type. The network modelling the interdependency among the risk factors is constructed by using a Naïve Bayesian Network (NBN) and validated by sensitivity analysis. The results reveal that the common risk factors among different types of accidents are ship operation, voyage segment, ship type, gross tonnage, hull type, and information. Scenario analysis is conducted to predict the occurrence likelihood of different types of accidents under various situations. The findings provide transport authorities and ship owners with useful insights for maritime accident prevention.

Keyword: Maritime safety, Accident analysis, Risk factors, Bayesian networks

1. Introduction

Waterborne transportation accounts for approximately 90% of the world trades in volume, representing one of the essential transportation modes in ensuring the prosperity of internatioanl tarde and global economy. Maritime accidents reveals new features in the past years. According to the 'Safety and Shipping' Annual Report of 2017 [1], published by Allianz Global Corporate & Specialty, there is more than a quarter of ship losses in 2016 occurred in the South China, Indochina, Indonesia and Philippines regions. Although the number of maritime casualties has declined over years, there is increasing complexity of navigation risk exposed in the shipping industry (e.g. high demand on human reliability in complicated operations introduced by advanced technologies). A study of the onboard duties and off-board entities involving Greek-flagged ships during 1993-2006 indicated that 57.1% of all accidents were attributed to human element [2]. Among them, 75.8% of accidents were detected onboard, and 80.4% of the onboard human-induced accidents were related to errors and violations of the ships' masters. There are numerous reasons for an individual to make errors, which may include communication failure, ineffective training, memory lapse, inattention, poorly designed equipment, exhaustion or fatigue, situation ignorance, noisy working conditions, and other personal and environmental factors (e.g. Fan, Zhang [3]). The questionnaire survey on maritime operations conducted by Safahani [4] emphasised the non-technical skills: 75% stated that a team leader should discuss the work plan with his/her teammates; 90% thought that monitoring the task provided an essential contribution to effective team performance; almost everyone in the survey believed that communication was a significant factor, and that teams who do not communicate effectively would increase the possibility of making errors. Branch, House [5] disclosed that watchkeeper manning levels and a master's ability to discharge his duties were significant factors influencing collisions and groundings.

Studies on maritime accident analysis rely on the discretional context and experts' knowledge to extract the causal relations among the process of accidents, as well as data-driven methodologies. Specifically, casual relations were connected to one type of accidents through accident analysis methods, specifically for grounding or collision [6-8]. Moreover, some studies focused on the probability or the frequency of maritime accidents. Fabiano, Currò [9] investigated the occupational accident frequency affected by the organisation, job experience, and productivity. Pristrom, Yang [10] estimated the likelihood of a ship being hijacked in the Western Indian or Eastern African region by using the Global Integrated Shipping Information System (GISIS) database together with expert judgement. Other studies concentrated on the severity or the consequence of maritime accidents. Zhang, Teixeira [11] predicted the accident consequences in the Tianjin port by statistical analysis of historical accident data. Wang and Yang [12] analysed the key risk factors influencing waterway accident severity by using Bayesian Networks (BN). In addition, some studies investigated the combination of the above two (i.e. likelihood and consequence) [13, 14]. However, few studies have been carried out to investigate the issues on how risk factors affect maritime accident types, leaving a research gap to fulfil for effective accident prevention. The key factors contributing to collisions are quite different from those resulting in groundings. In addition, understanding differentiation among the key factors contributing to different types of accidents will help generate useful insights for rational risk control measures.

This study aims at investigating how different risk factors generate, in an individual or combined manner, an impact on different types of maritime accidents in terms of likelihood. Manual case by base analysis of recorded maritime accidents from Marine Accident Investigation Branch (MAIB) and Transportation

Safety Board of Canada (TSB) that occurred from 2012 to 2017 is undertaken to develop a primary database to support this study, as they are among the most representative from the literature [15-17]. A BN-based approach is proposed to analyse accident types in maritime transport. To do so, the rest of the paper is structured as follows. The literature review on risk factors associated with maritime transport and BN-based risk analysis is conducted and presented in Section 2. Section 3 describes the methodology of Risk Influence Factors (RIFs) identification and BN modelling. Section 4 analyses the results of the most important RIFs with respect to different 'accident types' and highlights the implications through scenario analysis. Finally, conclusions are summarised in Section 5.

2. Literature review

2.1 Risk factors in maritime transportation

Ship accidents are caused by various types of failures, e.g. deck officer error (26%), equipment failure (9%), structural failure (9%), crew error (17%), mechanical failure (5%), among others. [18]. The factor that influences the risk level of maritime transport is defined as risk influence factor (RIF). To determine the risk factors of maritime transport, the latest related literature and maritime accident reports during 2012-2017 have been reviewed.

To determine the RIFs in maritime transportation, risk factors that were commonly presented or frequently described in accident reports were extracted. Such factors, complemented by the RIFs identified from the related literature, compose the maritime transport RIFs in this study, which are presented in Table 1.

Table 1 RIFs contributing to maritime transport accidents.

RIFs	**Literature sources**
Ship type	Weng and Yang [19], Heij and Knapp [20]
Hull type	Wang and Yang [12], Balmat, Lafont [21]
Ship age (years)	Balmat, Lafont [21], Zhang, Yan [22]

Length (metres)	MAIB19-2017, TSBM16P0362
Gross tonnage (GT)	Balmat, Lafont [21], Zhang, Yan [22]
Ship operation	MAIB19-2017
Voyage segment	MAIB19-2017
Weather condition	MAIB19-2017, MAIB8-2013
Sea condition	MAIB22-2017, MAIB19-2017, MAIB24-2016, TSBM16P0362
Fairway traffic	MAIB23-2017, MAIB18-2015, TSBM15C0006
Ship speed	Wang and Yang [12], Balmat, Lafont [14] MAIB20-2017, MAIB14-2013
Vessel condition	MAIB23-2017, MAIB20-2017, MAIB19-2017
Equipment/device	MAIB23-2017, MAIB22-2017, MAIB11-2017, TSBM15C0006, TSBM14P0014, TSBM14C0106
Ergonomic design	MAIB18-2015, MAIB26-2013, MAIB9-2013, TSBM16P0362, TSBM16C0005, TSBM14C0045
Information (whether effective and updated information provided)	MAIB23-2017, MAIB22-2017, MAIB19-2017, TSBM16P0362, TSBM16C0005, TSBM15C0006

Previous studies relied mainly on secondary database for risk factor identification in which primary information from accident reports was absence. One of the new features of this study is to incorporate new risk factors derived from accident reports into maritime accident analysis.

2.2 Risk analysis of maritime accidents

Since the UK Maritime and Coastguard Agency (UK MCA) proposed the formal safety assessment (FSA) framework to International Maritime Organization, maritime accident risk models have been fast developed because of the goal-setting risk regime. It takes into account ship conditions, organisational management, human operation, and hardware [18]. To assess the risks in maritime systems, quantitative risk assessments have been conduted to analyse maritime accidents. Yip, Jin [23] applied econometrics method to conclude that the number of passenger injuries is positively related to the number of crew injuries in ferry, ocean cruise and river cruise passenger vessel accidents. Talley and Ng [24] proposed a logical approach to select quality-of-service measures for port cargo, vessel and vehicle services, which can be used as port performance indicators for evaluating the service performance of multi-service ports. Ventikos and Psaraftis [25] presented the relationship between an oil spill-assessing approach, namely the event-decision network (EDN) and the FSA to describe the spill-scenario analysis and to pinpoint its interconnections with the official instrument. Besides that, risk analysis of maritime accidents would benefit the decision making systems onboard. Balmat, Lafont [21] presented a fuzzy approach to automatically define an individual ship risk factor, which could be used in a decision-making system. Wu, Zong [26] integrated evidential reasoning and TOPSIS into group decision-making for handling ships that are not under command. A fuzzy logic based approach was proposed by Wu, Yip [27] for ship-bridge collision alert, considering ship particulars, bridge parameters and natural environment, which can be used for improvement of the ship handling in the bridge waterway area. Moreover, the causation analysis and modelling of maritime risks have been conducted [28, 29]. Kum and Sahin [17] used Root Cause Analysis (RCA) to clarify the causes and applied Fuzzy Fault Tree Analysis (FFTA) for a recommendation to reduce the occurrence probabilities of maritime accidents. Also, Zhang, Yan [30] estimated the navigational risk of the Yangtze River using BN approach. Montewka, Ehlers [31] developed the risk framework using BN for the estimation of the risk model parameters.

Analysis of maritime accident database is one of the most effective ways to investigate the causal chains and the correlations among causal factors in risk assessment. Pristrom, Yang [10] used the Global Integrated Shipping Information System (GISIS) database to estimate the likelihood of a ship being hijacked. Zhang, Teixeira [11] analysed historical accident data from 2008 to 2013 to predict the accident consequences in Tianjin port. However, the maritime accident database contains limited information compared to maritime accident reports. The investigation reports of maritime accidents provide the navigation information, process of event occurrence, direct or indirect causes of the accidents, the actions taken during the accidents, and recommendations. A few studies utilised accident reports to conduct accident analysis due to the time-consuming process of extracting the data from each report. For instance, Wang and Yang [12] analysed the key risk factors influencing waterway accident severity from all accident investigation reports by China's Maritime Safety Administration (MSA). Chauvin, Lardjane [15] concerned 39 vessels involved in 27 collisions to show the importance of Bridge Resource Management for situations of navigation in restricted waters. Chen, Wall [32] utilised the accident reports of the selected cases from MAIB for accidents analysis to provide a complement measure. Akhtar and Utne [33] conducted a correlation analysis of fatigue-related factors identified from 93 accident investigation reports, and identified the most influential factors related to top management: vessel certifications, manning resources, and quality control.

The data acquisition through the investigation of accident reports brings new insights, which cannot be achieved from the existing databases. Integrating the primary data with the advanced quantitative BN analysis approach facilitates maritime accident analysis and prevention from an innovative perspective. Despite previous attempts of using BN to model objective data from accident reports[12], the relevant investigation relied on a small scale of database constrained in a pre-defined water/region. It requires more experiments based on a wide range of maritime accident data to be conducted to generalise the finding on BN’s feasibility on RIF analysis and more importantly to reveal the most important RIF from a global perspective, particularly with respect to different accident types.

2.3 Bayesian networks in maritime risk analysis

The interest of using BN as a tool in scientific risk analysis is continuously increasing, primarily related to its advantages in terms of learning and inference. According to the literature review by Weber, Medina-Oliva [34], the number of academic papers on BN in risk analysis increased every year. Compared with other classical methods applied to dependability analysis, e.g. Markov Chains (MC) and Fault Trees (FT), BN sustains its advantages. Specifically, FT allows for calculating the probability by binary decision diagrams (BDD), which models the dependencies between events. However, it cannot represent the multiple state variables when multiple failures result in different consequences in a system. On the contrary, BN displays similar capabilities as the FT, but has additional ability to model a multi-state variable and several output variables. Weber, Medina-Oliva [34,] Khakzad, Khan [35] presented a comparison of FT and BN approaches, while previous studies also explained how FT could be transformed into BN [36-38], involving dynamic FT transformation [39]. As far as MC is concerned, it analyses the exact probability of a failure event with the dependencies among variables and integrates the knowledge to represent multi-state variables. However, the system modelling tends to be sophisticated with increasing variables [34]. In light of this characteristic, BN has required a relatively low number of parameters and a small-size conditional probability table. BN is widely utilised in maritime risk analysis, e.g. ship navigational risk assessment, port safety assessment, Arctic water transportation, inland waterway transportation, and collision assessment [11 40 41 42 6, 43]. It is proved to be powerful to model maritime accidents since it enables quantitative analysis of Human and Organisational Factors (HOFs) [33, 44, 45]. It explicitly reveals probabilistic dependencies between factors and their causal relationships. Moreover, the feature that BN can take advantage of experts' knowledge makes it suitable for maritime risk modelling, in case of that failure data in the relevant investigations are incomplete. Therefore, experts' knowledge continues to be an essential data source for shipping accident modelling [41, 46], although it is subjectivity associated.

To avoid the subjective input in BN-model, a plain machine learning algorithm, the Naïve BN (NBN), is applied in the study. Due to its efficiency with the core idea of classification, the NBN model enables the simplified BN structures without sacrificing its accuracy.

Compared with the studies on the probability and/or the frequency of maritime accidents, those addressing the relationship between risk factors and accident types are scanty in the literature. The risk factors contributing to collision may be different from the risk factors contributing to sinking. It reveals another new feature that is the analysis of accident types in maritime transportation and a new understanding of differentiation among critical factors contributing to different types of accidents.

3. Methodology

BN is a probabilistic directed acyclic graphical (DAG) model [47], which is composed of nodes with the links between them, representing variables and influences of one node on the other(s), respectively. The directional arc from node *A* to node B refers that variable *A* has a direct causal effect on *B*, representing conditional dependencies. In addition, the nodes that are not directly linked are conditionally independent of each other. A BN model usually consists of the following steps: data acquisition, BN structure learning, BN analysis, and sensitivity analysis and model validation [22]. For applying the model into this study, a methodology is developed by the following steps.

3.1 Data acquisition

To begin with, it is necessary to conduct a systematic procedure to search the maritime accident reports and select the reviewed reports, referring to Macrae [7,] Uğurlu, Köse [8,] Chauvin, Lardjane [15,] Wan, Yang [48]. The procedure consists of three stages: (1) online database searching; (2) reports screening and selecting; (3) refining and analysis. In this process, some of the reports involving accidents due to disobeying rules of passengers or drowning in the swimming pool occurred in cruise ships, and extreme accidents occurred in small fishing vessels, tugs and etcetera were discarded, as their reduced manning requirements will easily lead to a distortion of results about the investigation on the factor impact [2]. Then, the maritime accident data is obtained according to the filtered accident reports.

3.2 RIF identification

With respect to RIFs in maritime accidents, it is necessary to identify the key factors from accident investigation reports. According to the filtered reports (in Section 3.1), we derived the risk factors among them according to their appearance frequency in accident reports to eliminate the factors of trivial effect (i.e. appearing less than twice across the whole searching reports). As a result, 16 RIFs are identified including Ship type, Hull type, Ship age (years), Length (metres), Gross tonnage (GT), Ship operation, Voyage segment, Weather condition, Sea condition, Time of day, Fairway traffic, Ship speed (knots), Vessel condition, Equipment/device, Ergonomic design, Information. The detailed explanation of RIFs in BN is stated in Section 4.2.

3.3 BN structure learning

Once RIFs are identified, a BN structure is to be generated by using the RIFs as the nodes. There are mainly two approaches for BN structure learning. One is based on the expert knowledge, which is used to conduct a qualitative analysis based on the subjective causal relationships. The other is the data-driven approach to represent the interactive dependencies between variables. This study is to develop the BN modelling by the later method.

However, the complexity of a data-driven BN structure super-exponentially increases with the growing number of variables in the network [40, 49]. To overcome such a disadvantage, NBNs are usually applied instead. It is a commonly used model aiming at improving the classification [50]. To realize this, there is a strong assumption in most NBN models that it has an independent node as the target node directly connected with all the other nodes which are independent to each other in the structure. Referring to the expert opinion and the previous studies[12], the interdependency among RIFs are insignificant in this study, which make it applicable for such strong assumption.

In the study, the only child node of BN is 'accident type', i.e. the class variable (S). The parent node set $R = \{R_{ST},\ R_{HT},\ R_{SA},\ R_{L},\ R_{GT},\ R_{SO},\ R_{VS},\ R_{WC},\ R_{SC},\ R_{TD},\ R_{FT},\ R_{SS},\ R_{vc},\ R_{E},\ R_{ED},\ R_{I}\}$ is the set of risk variables (R_k) including the 16 RIFs of (in a matching order) ship type, hull type, ship age, length, gross tonnage, ship operation, voyage segment, weather condition, sea condition, time of day, fairway traffic, ship speed, vessel condition, equipment, ergonomic design, and information. Then, the structure learning is simplified to demonstrate the relationship between S and R_k, as presented in Fig.1.(a).

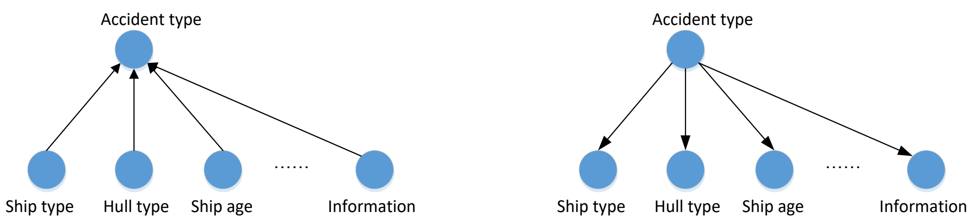


Fig. 1. (a). 'Accident type' as a child node Fig. 1.(b). 'Accident type' as a parent node.

However, the size of the conditional probability table of the target node increases exponentially, resulting in the complex computation in this converging BN. To simplify the structure, a modified diverging NBN structure in which 'Accident type' have no parents but is the only parent of other RIFs is presented, as shown in Fig. 1(b). Compared to the structure in Fig. 1(a), this structure (i.e. Fig. 1(b)) significantly reduces the computation and number of conditional probability distributions. Hence, it is adopted to express the relationship between the RIFs in the NBN structure. Because BN has the ability to conduct bi-directional risk analysis, the transformation from the converging to diverging connections will be well reflected by the adapted conditional probability tables (CPT) and hence has no influence to the final BN results on risk analysis (e.g. Wang and Yang [12]).

3.4 Mutual information and sensitivity analysis

3.4.1 Mutual information

In the probabilistic theory, the mutual information is a measure of the mutual dependence between two variables. It describes the amount of information obtained about one random variable, through the other random variables [40]. Mutual information is also interpreted as entropy reduction, measuring the mutual dependence of different variables. Since the objective of this study is to identify the relationship between RIFs and 'accident type', 'accident type' is determined as the fixed variable in mutual information. The larger the value of mutual information is, the stronger relationship between individual RIF and 'accident type'. In this way, calculating the mutual information is able to filter out the RIFs that are relatively less important in the model. Then the remaining RIFs are selected as significant variables with regards to a pre-defined accident type.

3.4.2 Sensitivity analysis - True Risk Influence (TRI) of risk variables

Based on the significant RIFs screened from mutual information calculation, there is another form of sensitivity analysis, e.g. scenario simulation, to determine the effects of different variables, particularly in a combined way. The classical way is to set a scenario in which all the other nodes (apart from the investigated ones) are locked, and the target node is updated accordingly. It means, for example, 10% up and down for the node reveals the effects of the variable in the model. It is considerably applicable for variables with two states, but not suitable for variables with more than two states. For example, when the state value of a bi-stated variable is increased from 0% to 10%, the value of the other state will decrease from 100% to 90% accordingly. However, the integration of the other states of multi-state variables makes it difficult to appropriately decrease their values when a selected state increases its value by 10%. In this case, the traditional scenario simulation is inappropriate.

In order to overcome the drawback of the traditional way, a new method proposed by Alyami, Yang [51] is applied here. This method increases the probability of the state within the highest influencing on a type of accidents (e.g. collision) to 100% to obtain the High Risk Inference (HRI) of collision. Then it increases the probability of the state generating the lowest influence on the collision to 100% to obtain the Low Risk Inference (LRI) of collision. In this way, calculating the average value of HRI and LRI concludes the True Risk Influence (TRI) of each variable in the case of a particular accident type. It is described as:

$$TRI = \frac{HRI + LRI}{2} \quad (1)$$

where HRI refers to 'High Risk Inference' which is calculated for a variable influencing 'collision' , LRI is 'Low Risk Inference' calculated for a variable influencing 'collision', and TRI refers to 'True Risk Influence' for a variable influencing 'collision'. To obtain the variable influence on 'accident type', a similar analysis procedure is applied to other accident types, 'grounding' and 'flooding', etc. Then TRIs for a variable influencing all accident types are obtained. After applying this method for each variable, the TRIs for all variables for all accident types are available. Therefore, the sensitivity analysis illustrates the ranking of variables' influences on accident types according to the value of TRI. In addition, the average TRI values of all accident type priorities the variables' effects on the 'accident type'. The higher a TRI is, the higher its corresponding RIF's effect on 'accident type'.

4. Results and discussion

4.1 Raw data

The accident reports are from MAIB in UK and TSB in Canada, as they are among the most representative from the literature [15-17]. The raw data derived from the MAIB and TSB contains general information of the ship and the voyage, accident evolution process, and details related to the management and organizational factors. In the screening process stage, the accident reports were screened with a focus on errors-related accidents to ensure their representativeness and relevance. Some of the reports involving accidents due to disobeying rules of passengers or drowning in the swimming pool occurred in cruise ships, and extreme accidents occurred in small fishing vessels, tugs and etcetera were discarded, as their reduced manning requirements will easily lead to a distortion of results about the investigation on the accident [2]. In the final stage, these reports had been further refined and analysed, especially the 'safety issues' and 'common factors' Section in the accident reports. Some details of information associated with the accident process were involved in the refinery. According to such analysis, there are 109 accident reports extracted from 152 reports in MAIB and 52 accident reports obtained from 61 reports in TSB, as shown in Appendix I.

In total, the 161 maritime accidents involving 208 vessels reported in MAIB and TSB between Jan. 2012 and Dec. 2017 were carefully reviewed and analysed manually. The search was conducted in Jan. 2018 and the general statistical analysis and findings are presented in Fig. 2 and Fig. 3(a) (b), which provide the raw data for our next in-depth analysis using NBN.

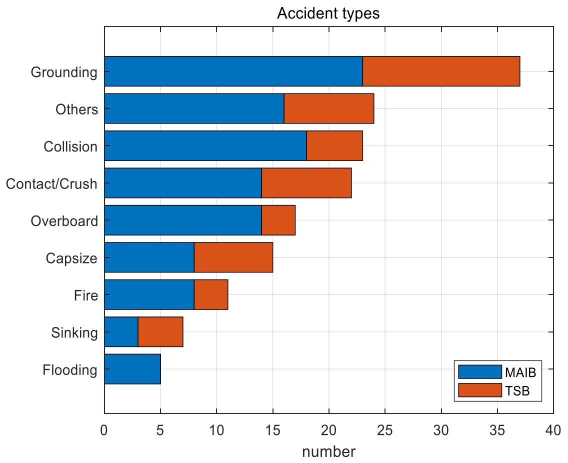
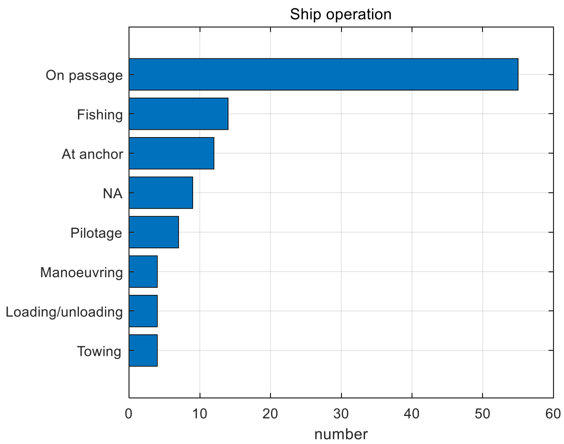
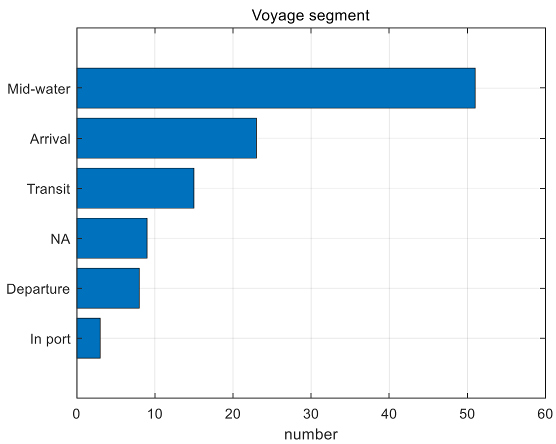


Fig. 2. Accident distribution by accident types



(a) Accident distribution by ship operations



(b) Accident distribution by voyage segments

Fig. 3. Accident distribution from MAIB

As is indicated in Fig. 2, grounding, collision and contact/crush accounted for larger percentages than other kinds of accidents while sinking and flooding accounted for lower percentages. Specifically, there were 23 grounding accidents from MAIB and 14 from TSB, while 3 sinking accidents from MAIB and 4 from TSB. And Fig. 3 shows accident distributions by ship operation and voyage segment from MAIB. The number of accidents happened on passage was much higher than that others, followed by 'fishing' and 'at anchor'. However, the number of accidents happened in mid-water was much higher than others like 'departure' and 'in port'.

These reports had been further refined and analysed. And special attention are paid to the 'safety issues' and 'common factors' in the accident reports. Some details of information associated with the accident process were involved in the refinery. According to such analysis, the common factors contributing to the accidents are generated.

4.2 RIF identification

With respect to the accident type, a maritime accident can be classified into collision (*S1*), grounding (*S2*), flooding (*S3*), fire/explosion (*S4*), capsize (*S5*), contact/crush (*S6*), sinking (*S7*), overboard (*S8*), and others (*S9*), which refers to the combined description and definition in MAIB and TSB. These 9 types of accidents consists of 9 states ($S1$~ $S9$) of the variable 'accident type' in the study.

Furthermore, the accident-related RIFs are retrieved in Table 2. In the quantitative analysis of BN modelling, the accident type is defined as a dependent variable, variables in Table 2 are defined as independent variables, as explained in Section 3.3.

Table 2 The accident-related RIFs

RIFs	**Notation**	**Description**	**Values of state in BN**
Ship type	R_{ST}	Passenger vessel, tug, barge, fishing vessel, container ship, bulk carrier, RORO, tanker or chemical ship, cargo ship, others.	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Hull type	R_{HT}	Steel, wood, aluminium, others	1, 2, 4, 5
Ship age (years)	R_{SA}	(0 5], [6 10], [11 15], [16 20], >20, NA	1, 2, 3, 4, 5, 6

Length (metres)	R_L	≤100, >100, NA	1, 2, 3
Gross tonnage (GT)	R_{GT}	≤300, 300 to 10000, >10000, NA	1, 2, 3, 4
Ship operation	R_{SO}	Towing, Loading/unloading, Pilotage, Manoeuvring, Fishing, At anchor, On passage, others	1, 2, 3, 4, 5, 6, 7, 8
Voyage segment	R_{VS}	In port, Departure, Arrival, Mid-water, Transit, others	1, 2, 3, 4, 5, 6
Weather condition	R_{WC}	Good or poor considering rain, wind, fog, visibility	1, 2
Sea condition	R_{SC}	Good or poor considering falling/rising tide, current, waves	1, 2
Time of day	R_{TD}	07:00 to 19:00, other	1, 2
Fairway traffic	R_{FT}	Good or poor considering complex geographic environment, dense traffic, or receptive nature of the route contributing to ignorance	1, 2
Ship speed*	R_{SS}	Normal, Fast	1, 2
Vessel condition	R_{vc}	Good condition of vessels, or the condition of vessel has nothing to do with the accidents; Poor condition of vessels, or increasing complexity of propulsion arrangements, or modification made to vessels and size contributes to the accidents	1, 2
Equipment/device	R_E	Devices and equipment on board operate correctly; Devices and equipment not fully utilised or operated correctly (e.g., BNWAS switched off, alarm system not in the recommended position or not noticed)	1, 2
Ergonomic design	R_{ED}	Ergonomic friendly or ergonomic aspects has nothing to do with accidents; ergonomic impact of innovative bridge design (e.g., visual blind sector ahead, motion illusion)	1, 2
Information	R_I	Effective and updated information provided; Insufficient or lack of updated information (e.g., poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment, without working indicators or light for necessary observing)	1, 2

RIFs: risk influence factors; BN: Bayesian network; RORO: roll on/roll off; NA: not applicable; BNWAS: bridge navigational watch alarm system; MAIB: Marine Accident Investigation Branch.

*The ship speed is group into normal and fast states based on the description in the MAIB accident reports.

A majority of definitions of variables' states are derived from accident reports. To quantify such states, majority of variables are defined and quantified based on the literature in Table 1. However, variables, e.g. accident type, ship type, hull type, ship operation, and voyage segment, are divided into different states according to the classification of MAIB or TSB investigation. The 'vessel condition' is quantified into two states based on whether it is blamed for the faults in accidents, as described in the reports. The grading of 'ship speed' is based on the description in the MAIB accident reports, rather than the grading method by Wang and Yang [12]. The main reason is that accurate speeds of vessels involved in accidents are not clearly indicated in the source database.

4.3 NBN modelling

Although the assumption that the variables are completely independent is not always true in reality, modified diverging NBN simplifies the structure by reducing the number of conditional probability distributions. Moreover, such an assumption does not significantly affect the posterior probabilities calculated, which does not affect the scenario analysis in the study [12], given the fact that the statistical analysis of all the accidents did not indicate strong correlation among the RIFs. Therefore, assuming that all the variables, i.e. the child nodes, are independent with each other, the NBN is constructed.

Based on the NBN model, the parameter learning of CPTs from the cases is conducted by the software 'Netica' using the counting-learning algorithm. Once the CPTs are constructed and obtained (Appendix II), the posterior probabilities of each variable can be calculated. The statistical analysis of the probability of variables reveals interesting initial findings in terms of safety caution and accident prevention as follows.

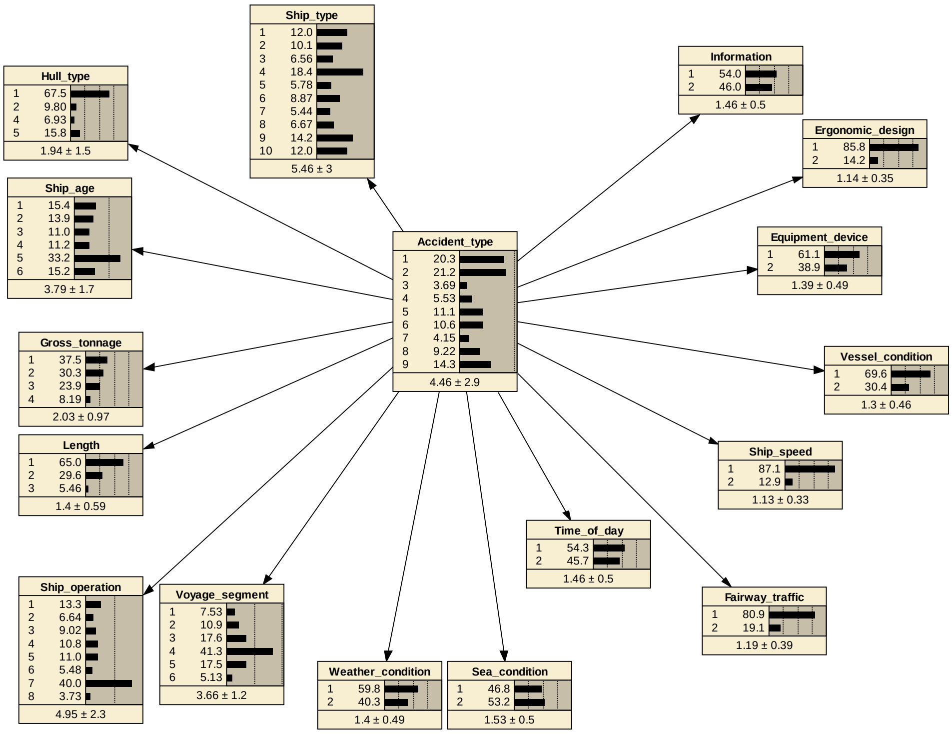


Fig. 4. Results of NBN

Fig. 4 presents the results of NBN involving all the retained 16 RIFs. Among the accidents, grounding and collision are two most frequently occurred types of accidents: accounting for 20.3% and 21.2%, respectively. A majority of vessel lengths (i.e., 65%) are less than 100*m*. Vessels with gross tonnages less than 300 account for 37.5% of shipments involved in accidents. In addition, 67.5% of vessels are made of steel.

In light of environmental factors, 40% of vessels in the accidents are involved in the ship operation of 'on passage', 41.3% are involved in the voyage segment of 'mid-water'. In addition, only 19.1% of ships involved in accidents are in poor fairway traffic in the process of accidents, 45.7% are at night time. Severe weather condition accounts for 40.2% of accidents, while tough sea condition accounts for 53.2%. With regard to ship factors, fishing vessels constitute the largest proportion (i.e. 18.4%) of shipments in accidents. Ships older than 20 years is presented in 33.2% of accidents. In addition, 46% of vessels convey insufficient information, 14.2% have ergonomic design problems, 38.9% are faced with invalid equipment or devices onboard, and 30.4% experience the condition of modification or increasing size.

4.4 Sensitivity analysis and model verification

4.4.1 Mutual information analysis

Table 3 demonstrates the mutual information shared between "accident type" and RIFs. When "accident type" is the parent node, "ship operation" with the corresponding mutual information value of 0.28294, has the strongest effect on the accident type. To select important variables, a threshold of the mutual information value is set as 0.09, which is the average mutual information value. The variables with $I(S,R_k)$ larger than 0.09, i.e. "ship operation", "voyage segment", "ship type", "gross tonnage", "hull type", and "information", illustrate essential impacts on "accident type". Thus, these variables are to be computed for the factor analysis in the next step. In addition, variables that have less impact on "accident type" mainly include "ship age", "vessel condition", "ergonomic design", "length", "fairway traffic", "sea condition", "equipment or device", "ship speed", "time of day", and "weather condition".

Table 3 Mutual information shared with 'accident type'

Node	Mutual Info.	Percentage	Variance of Beliefs
Accident_type	2.95073	100	0.7352824
Ship_operation	0.28294	9.59	0.0156048
Voyage_segment	0.21515	7.29	0.0076025
Ship_type	0.13632	4.62	0.0048136
Gross_tonnage	0.12415	4.21	0.0037518
Hull_type	0.10076	3.41	0.0024178
Information	0.09665	3.28	0.0032523
Ship_age	0.07052	2.39	0.0019386
Vessel_condition	0.06771	2.29	0.0010538
Ergonomic_design	0.05944	2.01	0.0030873
Length	0.05745	1.95	0.0009204
Fairway_traffic	0.05660	1.92	0.0022666

Sea_condition	0.05270	1.79	0.001587
Equipment_device	0.03650	1.24	0.0008695
Ship_speed	0.03372	1.14	0.0012873
Time_of_day	0.01941	0.658	0.000732
Weather_condition	0.01907	0.646	0.0009535

4.4.2 Sensitivity analysis

In terms of sensitivity analysis, Table 4 demonstrates the TRI value of 'ship operation' against collision, where *S*1 refers collision. Table 5 indicates the values of all RIFs for all accidents, where *S*1~ *S*9 are defined in Section 4.2.

Table 4 TRI of a risk variable (ship operation) for collision

Ship_operation											
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**S1***	**HRI**	**LRI**	**TRI**
/	/	/	/	/	/	/	/	20.30	19.50	17.31	18.41
100%	0	0	0	0	0	0	0	2.99			
0	100%	0	0	0	0	0	0	5.99			
0	0	100%	0	0	0	0	0	4.41			
0	0	0	100%	0	0	0	0	11.00			
0	0	0	0	100%	0	0	0	10.80			
0	0	0	0	0	100%	0	0	7.26			
0	0	0	0	0	0	100%	0	39.80			
0	0	0	0	0	0	0	100%	10.70			

*S1 - Collison

Table 5 TRI of risk variables for all accident types

Node	**TRI**									
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**Average**
Ship_operation	18.41	20.33	2.37	4.21	10.07	6.24	3.56	12.94	19.36	10.83
Voyage_segment	16.44	14.94	1.96	2.06	9.07	13.38	2.03	9.06	14.82	9.30
Ship_type	11.70	11.82	3.09	3.35	8.72	9.63	4.44	8.61	8.23	7.73
Gross_tonnage	5.35	11.90	1.70	1.19	7.59	6.01	3.58	3.89	4.10	5.03
Hull_type	7.00	7.30	3.91	8.23	4.67	3.47	4.02	9.41	8.51	6.28
Information	4.25	9.40	1.53	1.70	3.11	6.20	0.51	3.24	4.25	3.80

Specifically, in Table 4, the first row denotes the base-case scenario where the value of *S*1 is '20.3', and the following rows represent the different scenarios with each state of the variable reaches 100%, for example, the second row increases the probability of the state 1 of ship operation to 100% to obtain the value of *S*1 (2.99). The same process is applied to all states of ship operation. According to column 'S1', ‘39.8’ is the largest, which means the state 7 of ship operation is the state within the highest influencing on *S*1 (collision), and the difference between ‘39.8’ and ‘20.3’ (base-case scenario) is the HRI, i.e. ‘19.5’. However, ‘2.99’ is the smallest value, which means the state1 of ship operation is the state within the lowest influencing on *S*1 (collision), so the LRI is obtained as ‘17.31’. Then the TRI is calculated by averaging them. In this way, TRIs of each RIF of each accident type are obtained in Table 5.

To obtain the impact levels of such RIFs in accident types, TRIs are compared and ranked. Generally, the most important variables lists for ‘accident types’ are as follows:

Ship operation > Voyage segment > Ship type > Hull type > Gross tonnage > Information

In detail, the most important variables lists for different accident types are demonstrated in Table 6.

Table 6 The most important variables

Accident type	**Ship operation**	**Voyage segment**	**Ship type**	**Hull type**	**Gross tonnage**	**Information**
S1 Collision	1	2	3	4	5	6
S2 Grounding	1	2	4	6	3	5
S3 Flooding	3	4	2	1	5	6
S4 Fire/explosion	2	4	3	1	6	5
S5 Capsize	1	2	3	5	4	6
S6 Contact/crush	3	1	2	6	5	4
S7 Sinking	4	5	1	2	3	6
S8 Overboard	1	3	4	2	6	5
S9 Others	1	2	4	3	6	5

4.4.3 Model validation

To validate the model, another sensitive analysis is conducted by investigating the results of the model given RIFs. It is also used to test the combined effect of multiple RIFs to the accident types. There are two axioms that have at least to be satisfied for the inference process [22, 52]:

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

Axiom 2: The total influence of the combination of the probability variations of x parameters (evidence) should be no smaller than the one from the set of y ($y \in x$) risk factors.

Accounting for different states of the parent nodes, this study calculates the changed value of each state. The 'information' is selected as the first node, the state generating the highest changed value of state 1 in 'accident type' is increased by 10%, while the state generating the lowest changed value of state 1 in 'accident type' is decreased by 10%. This procedure is written as '~10%' in Table 7. Then, the same approach is applied to the next RIF, and the cumulative changed value is obtained and updated. The updating procedure would continue until all the RIF nodes are involved. Similarly, the same updating procedure is applied into the state 2, 3… 9 in 'accident type' respectively, until all states of accident type are included, as seen in Table 7.

Table 7 Accident rate of minor change in variables

Node	**Accident rate of minor change**						
Information	/	**~10%**	**~10%**	**~10%**	**~10%**	**~10%**	**~10%**
Hull type	/	/	**~10%**	**~10%**	**~10%**	**~10%**	**~10%**
Gross tonnage	/	/	/	**~10%**	**~10%**	**~10%**	**~10%**
Ship type	/	/	/	/	**~10%**	**~10%**	**~10%**
Voyage segment	/	/	/	/	/	**~10%**	**~10%**
Ship operation	/	/	/	/	/	/	**~10%**
S1	20.30	20.70	21.00	21.20	21.40	22.00	23.40
S2	21.20	22.20	22.60	23.40	23.60	24.20	24.60
S3	3.69	3.85	4.04	4.14	4.18	4.23	4.27
S4	5.53	5.71	5.90	5.96	6.01	6.08	6.17
S5	11.10	11.40	11.50	11.90	12.10	12.30	12.50
S6	10.60	11.30	11.40	11.70	11.80	12.20	12.30
S7	4.15	4.20	4.51	4.77	4.85	4.91	4.99
S8	9.22	9.57	9.84	10.10	10.40	10.50	11.00
S9	14.30	14.7	15.00	15.10	15.20	15.40	15.80

The first column of the data in Table 7 shows the original values of 9 states of accident types in NBN, and the rest columns state the updated changed values of results. However, each state of 'accident type' is calculated separately, i.e. each row is computed through the change of states of RIFs in each accident type. Specifically, for the first row, '20.30' is the original value of accident type *S*1 (grounding). Moreover, '20.70' is calculated by the way that the state of 'Information' generating the highest changed value of *S*1 is increased by 10% while the state generating the lowest changed value of *S*1 is decreased by 10%. A further step is conducted based on '20.70' to obtain '21.00' in the table, which means the state of 'Hull type' generating the highest changed value of *S*1 is increased by 10% while the state generating the lowest changed value of *S*1 is decreased by 10%. Then 'Gross tonnage', 'Ship type', 'Voyage segment', 'Ship operation' apply this method sequentially. Furthermore, the same updating procedure is applied into the *S*3, *S*4, …, *S*9 respectively, until accident types are included. Besides that, the updated values of the target node demonstrate this model is in line with Axiom 1. Moreover, Axiom 2 is examined by comparing the initial target value with the updated one under all states. From Table 7, the updated values of the target node are gradually increasing or decreasing along with the continuous updating of RIFs.

4.5 Implications: scenario analysis

The study enables the understanding of differentiation among critical factors contributing to different types of accidents. BN modelling is applicable to analyse the occurrence likelihood of each accident type in different scenarios involving vessel condition and environmental factors. To do this, two scenarios are proposed for useful research implications and managerial contributes.

4.5.1 Scenario 1: environmental factor

In the first scenario, maritime accidents under specific shipping environmental factors are estimated. Shipping environmental factors contain ship operation, voyage segment, weather condition, sea condition, time of day, fairway traffic in this scenario. For different assigned states of these factors, maritime accidents reveal in different types.

When the nodes are assigned with the specific states in Fig. 5(a), the effects of the shipping environment are revealed. The probability of collision is the highest among the ‘accident type’, accounting for 85.1%, followed by grounding only accounting for 4.52%. Such probability indicates the considerable increase in the risk of collision compared to the other types of accidents.

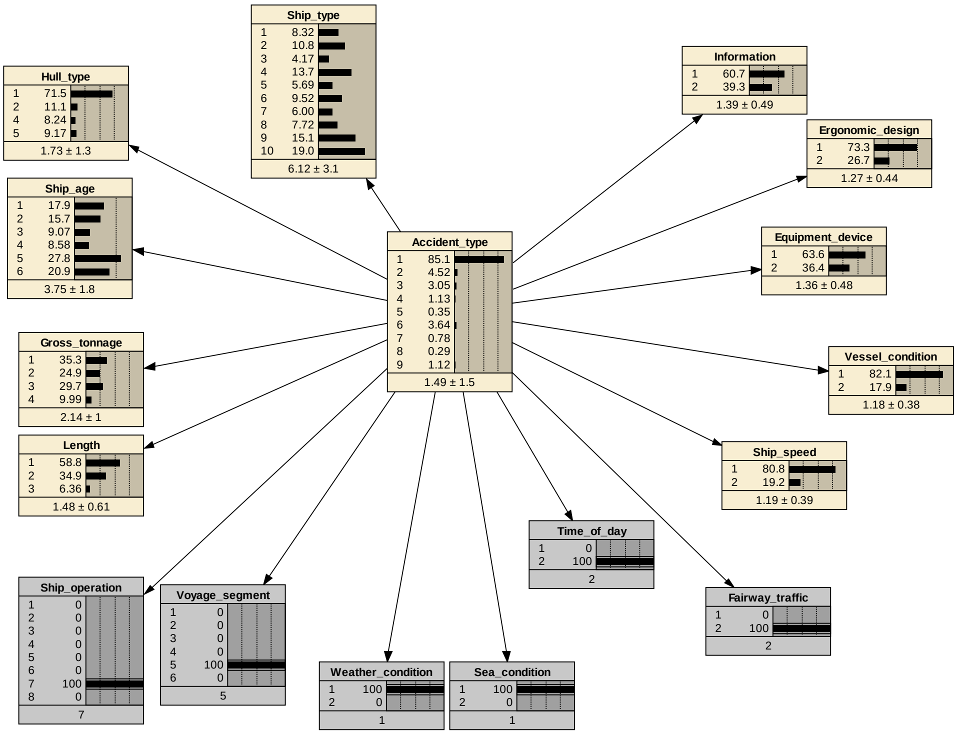


Fig. 5. (a). Posterior probability analysis in Scenario 1 - collision

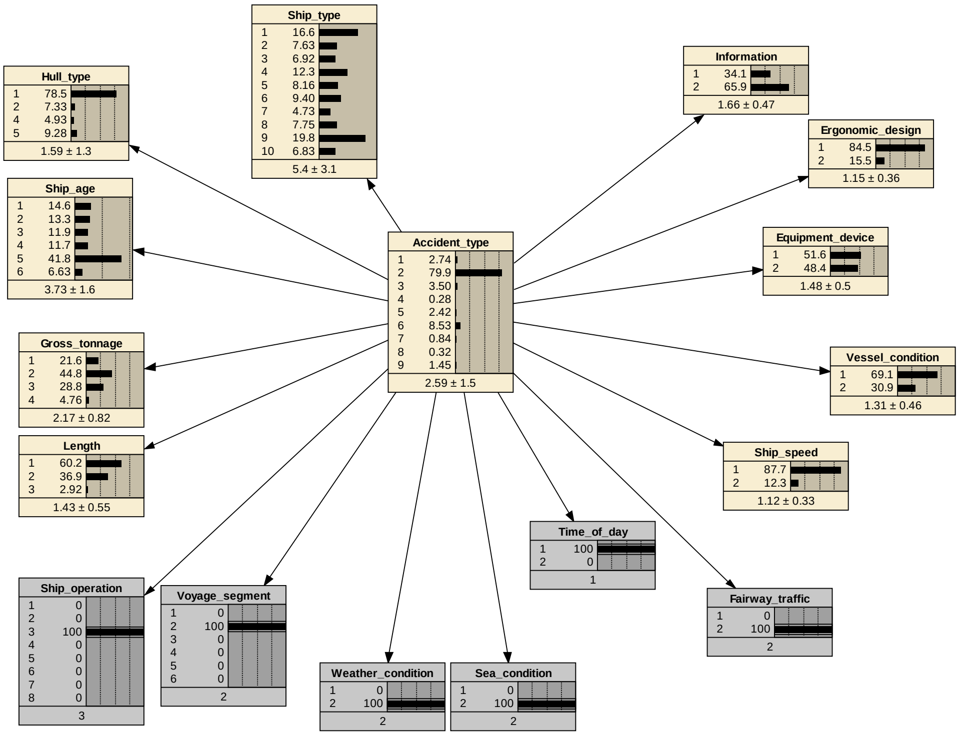


Fig. 5. (b). Posterior probability analysis in Scenario 1 - grounding

With regard to the following states in Fig. 5(b), the effects of the environment are revealed. The probability of grounding is the highest among the 'accident type', accounting for 79.9% of the accident types. Therefore, transport authorities and ship owners should pay more attention to risk-reduction measures for collision or grounding under specific navigational environment, especially the strong-related variables, i.e. ship operation, voyage segment, fairway traffic, and sea condition.

4.5.2 Scenario 2: vessel factor

In the second scenario, attention has been paid to vessel factors associated with maritime accident types. The variables include ship age, ship type, information, ergonomic design, equipment/device, vessel condition, and ship speed. For different assigned states of these vessel factors, maritime accident types have shown different likelihoods.

Assuming that variables are assigned with the certain states in Fig. 6(a), the effects of vessel factors on accident types are illustrated. The probability of collision is the highest among ‘accident type’, accounting for 82.1%. This probability indicates the considerable increase in the risk of collision compared to the initial states in Fig. 4 due to the combined effect of the involved RIFs.

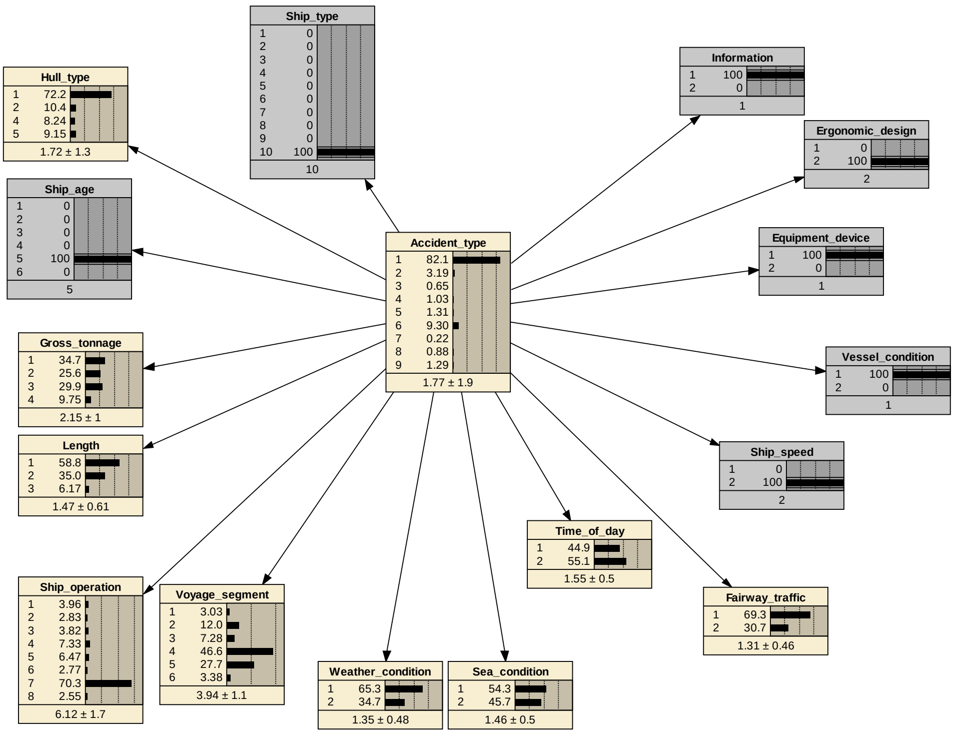


Fig. 6. (a). Posterior probability analysis in scenario 2 – collision

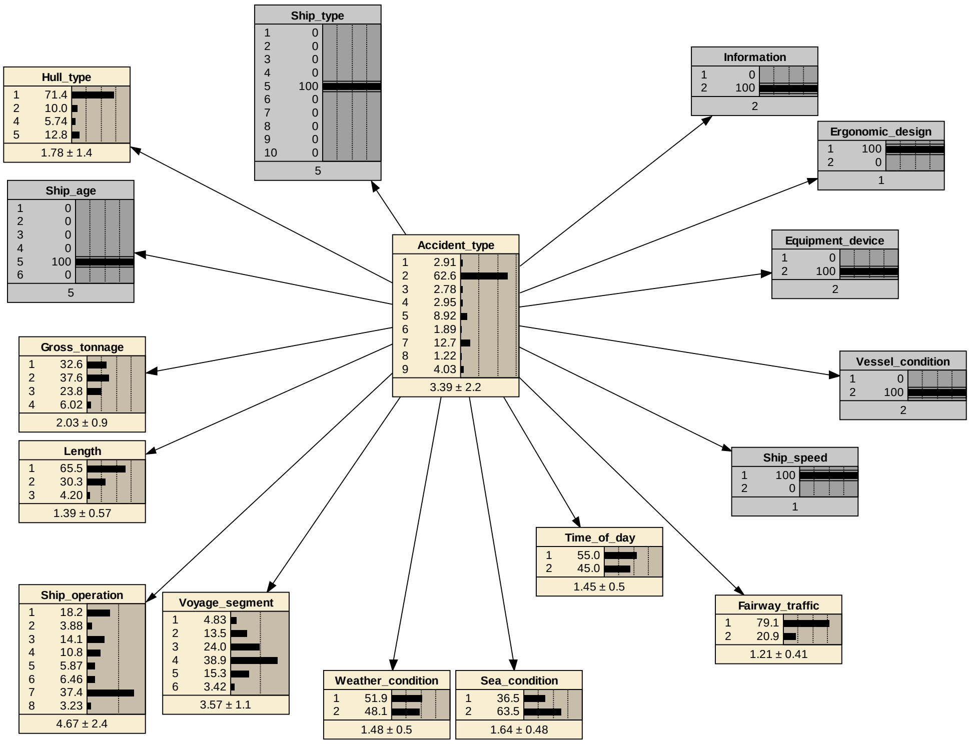


Fig. 6. (b). Posterior probability analysis in scenario 2 – grounding

Assuming that the variables are assigned with the specific states in Fig. 6(b), the effects of vessel factors are indicated. The probability of grounding is the highest among 'accident type', accounting for 62.6%, followed by sinking (i.e., 12.7%). This probability indicates the significant increase in the risk of grounding and sinking compared to the initial states in Fig. 4.

According to the above analysis, transport authorities and ship owners can use this findings to put forward the most effective risk control measures for different types of accidents derived from various vessel factors, especially the strong-related variables, i.e. ship type, information, ship age, vessel condition, and ergonomic design.

5. Conclusions

Compared to previous studies focusing on causal factors related to the severity and the probability of maritime accidents, this study uses a NBN approach to investigate how different risk factors pose an impact on different types of maritime accidents. To identify RIFs, maritime accident reports from MAIB and TSB within a five-year period are extracted and reviewed to develop a primary database on maritime accidents. Then the risk-based NBN model is constructed to analyse RIFs in maritime accidents. At last, the sensitivity analysis is conducted, as well as scenario analysis to implicate research contributes. In general, the results from the NBN model present the distinctions among the key factors contributing to different types of accidents, which helps generate insights for accident prevention.

In summary, the findings of this study can be summarised as follows:

(1) According to the calculations of the mutual information, crucial RIFs are ranked under different accident types. The results reveal that critical RIFs for maritime accident types are ‘Ship operation’, ‘Voyage segment’, ‘Ship type’, ‘Gross tonnage’, ‘Hull type’, ‘Information’.

(2) There is the highest probability of overboard occurred on fishing vessels. When the ship operation is ‘towing’, the accident type has high likelihood of being ‘capsize’; ‘manoeuvring’ and ‘on passage’ operation contribute to the higher probability of grounding; ‘pilotage’ is closely related to ‘contact/crush’.

(3) When ships are in ‘mid-water’ and ‘transit’ voyage segments, there is a higher probability of being in collision. Grounding is more easily to happen in ‘departure’ and ‘arrival’ segments.

(4) The situation of poor information onboard exposes a higher risk of grounding, whereas the condition of good information associates with the collision.

Among them, the scenario analysis reveals that environmental factors and vessel factors of maritime accidents generate significant impact on accident types.

With respect to the environmental factors, the probability of collision is the highest among the ‘accident type' when a ship is in the below states: 'voyage segment – transit'; 'ship operation - on passage'; 'before 7:00 am or after 19:00 pm'; 'good weather and sea condition'; 'not considering the fairway traffic appropriately'. The probability of grounding is the highest when a ship is in the below states: 'voyage segment – departure'; 'ship operation – pilotage'; 'between 7:00 am and 19:00 pm'; 'severe weather and sea condition'; 'not considering the fairway traffic appropriately'.

With regard to the vessel factors, the probability of collision is the highest among 'accident type' if a ship is in the following states: 'older than 20 years', 'effective and updated information provided', 'ergonomic problem', 'equipment operates correctly', 'good condition of vessel', 'fast ship speed'. The probability of grounding is the highest among 'accident type' if a fishing ship is in the following states: 'older than 20 years', 'lack if updated information', 'ergonomic design friendly', 'equipment not fully utilised', 'modification made to vessels and size', 'normal ship speed'. Therefore, such conclusions can effectively assist maritime authorities in developing countermeasures for accident prevention.

There are also limitations in this study. The small number of flooding data makes the results not significant and robust. Although BN has the ability to conduct bi-directional risk analysis, the transformation from the converging to diverging connections does not intuitively represent the accident development. Further research can be performed by using expert judgement to help model learning to overcome the problems brought by data scarcity. Moreover, more human factors resources, underlining communication, situation awareness, fatigue, and etcetera, will be processed to conduct further research to illustrate the influence of human errors on maritime accidents.

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Declaration of conflicting interests

The authors declare that there is no conflict of interest.

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Appendix I

Accident reports from MAIB and TSB

No	Code	Source	No	Code	Source
1	26-2017	MAIB	83	2-2014	MAIB
2	25-2017	MAIB	84	1-2014	MAIB
3	24-2017	MAIB	85	SB3/2014	MAIB
4	23-2017	MAIB	86	26-2013	MAIB
5	22-2017	MAIB	87	24-2013	MAIB
6	21-2017	MAIB	88	23-2013	MAIB
7	20-2017	MAIB	89	22-2013	MAIB
8	19-2017	MAIB	90	20-2013	MAIB
9	17-2017	MAIB	91	18-2013	MAIB
10	16-2017	MAIB	92	17-2013	MAIB
11	14-2017	MAIB	93	14-2013	MAIB
12	11-2017	MAIB	94	11-2013	MAIB
13	10-2017	MAIB	95	10-2013	MAIB
14	8-2017	MAIB	96	9-2013	MAIB
15	7-2017	MAIB	97	8-2013	MAIB
16	5-2017	MAIB	98	7-2013	MAIB
17	4-2017	MAIB	99	6-2013	MAIB
18	3-2017	MAIB	100	5-2013	MAIB
19	1-2017	MAIB	101	4-2013	MAIB

20	27-2016	MAIB	102	3-2013	MAIB
21	26-2016	MAIB	103	1-2013	MAIB
22	25-2016	MAIB	104	SB3/2013	MAIB
23	24-2016	MAIB	105	27-2012	MAIB
24	20-2016	MAIB	106	26-2012	MAIB
25	19-2016	MAIB	107	25-2012	MAIB
26	18-2016	MAIB	108	24-2012	MAIB
27	17-2016	MAIB	109	11-2012	MAIB
28	16-2016	MAIB	1	m16p0362	TSB
29	15-2016	MAIB	2	M16P0241	TSB
30	14-2016	MAIB	3	M16P0162	TSB
31	13-2016	MAIB	4	M16P0062	TSB
32	12-2016	MAIB	5	M16C0036	TSB
33	10-2016	MAIB	6	M16C0014	TSB
34	8-2016	MAIB	7	M16C0005	TSB
35	6-2016	MAIB	8	M16A0327	TSB
36	4-2016	MAIB	9	M16A0141	TSB
37	3-2016	MAIB	10	M16A0140	TSB
38	2-2016	MAIB	11	M16A0115	TSB
39	1-2016	MAIB	12	M15P0347	TSB
40	28-2015	MAIB	13	M15P0286	TSB
41	27-2015	MAIB	14	M15P0037	TSB
42	26-2015	MAIB	15	M15P0035	TSB
43	25-2015	MAIB	16	M15C0094	TSB
44	24-2015	MAIB	17	M15C0045	TSB
45	20-2015	MAIB	18	M15C0006	TSB
46	18-2015	MAIB	19	M15A0189	TSB
47	17-2015	MAIB	20	M15A0045	TSB
48	16-2015	MAIB	21	M15A0009	TSB
49	15-2015	MAIB	22	M14P0150	TSB
50	14-2015	MAIB	23	M14P0121	TSB
51	13-2015	MAIB	24	M14P0110	TSB
52	12-2015	MAIB	25	M14P0023	TSB
53	11-2015	MAIB	26	M14P0014	TSB
54	10-2015	MAIB	27	M14C0219	TSB
55	9-2015	MAIB	28	M14C0193	TSB
56	7-2015	MAIB	29	M14C0156	TSB
57	6-2015	MAIB	30	M14C0106	TSB
58	5-2015	MAIB	31	M14C0045	TSB
59	3-2015	MAIB	32	M14A0348	TSB
60	1-2015	MAIB	33	M14A0289	TSB

61	32-2014	MAIB	34	M14A0051	TSB
62	31-2014	MAIB	35	M13W0057	TSB
63	30-2014	MAIB	36	M13N0014	TSB
64	29-2014	MAIB	37	M13N0001	TSB
65	28-2014	MAIB	38	M13M0287	TSB
66	25-2014	MAIB	39	M13M0102	TSB
67	24-2014	MAIB	40	M13L0185	TSB
68	21-2014	MAIB	41	M13L0123	TSB
69	19-2014	MAIB	42	M13L0067	TSB
70	18-2014	MAIB	43	M13C0071	TSB
71	17-2014	MAIB	44	M12W0207	TSB
72	16-2014	MAIB	45	M12W0070	TSB
73	15-2014	MAIB	46	M12N0017	TSB
74	13-2014	MAIB	47	M12L0147	TSB
75	12-2014	MAIB	48	M12L0098	TSB
76	11-2014	MAIB	49	M12L0095	TSB
77	10-2014	MAIB	50	M12H0012	TSB
78	9-2014	MAIB	51	M12F0011	TSB
79	8-2014	MAIB	52	M12C0058	TSB
80	7-2014	MAIB			
81	6-2014	MAIB			
82	4-2014	MAIB			

Appendix II

Conditional probability tables (CPT) for RIFs

	Ship type									
Accident type	1	2	3	4	5	6	7	8	9	10
1	7.5472	11.3207	3.7736	13.2076	5.6604	9.4340	5.6604	7.5472	15.0943	20.7547
2	18.1818	7.2727	7.2727	10.9091	9.0909	9.0909	3.6364	7.2727	21.8182	5.4546
3	5.8824	5.8824	5.8824	23.5294	5.8824	11.7647	11.7647	11.7647	11.7647	5.8824
4	9.5238	9.5238	4.7619	23.8095	4.7619	4.7619	9.5238	4.7619	19.0476	9.5238
5	6.0606	18.1818	9.0909	30.3030	6.0606	6.0606	3.0303	6.0606	3.0303	12.1212
6	12.5000	6.2500	3.1250	12.5000	3.1250	12.5000	12.5000	12.5000	12.5000	12.5000
7	11.1111	11.1111	16.6667	22.2222	5.5556	5.5556	5.5556	5.5556	5.5556	11.1111
8	10.3448	6.8966	3.4483	41.3793	6.8966	3.4483	3.4483	3.4483	10.3448	10.3448
9	17.5000	12.5000	10.0000	12.5000	2.5000	12.5000	2.5000	2.5000	15.0000	12.5000

Equipment_ device

Accident type	1	2
1	64.4445	35.5556
2	48.9362	51.0638
3	66.6667	33.3333
4	69.2308	30.7692
5	60.0000	40.0000
6	62.5000	37.5000
7	30.0000	70.0000
8	80.9524	19.0476
9	65.6250	34.3750

Ergonomic design		
Accident type	1	2
1	71.1111	28.8889
2	85.1064	14.8936
3	88.8889	11.1111
4	92.3077	7.6923
5	96.0000	4.0000
6	75.0000	25.0000
7	90.0000	10.0000
8	95.2381	4.7619
9	96.8750	3.1250

Fairway traffic		
Accident type	1	2
1	66.6667	33.3333
2	74.4681	25.5319
3	66.6667	33.3333
4	92.3077	7.6923
5	92.0000	8.0000
6	79.1667	20.8333
7	90.0000	10.0000
8	95.2381	4.7619
9	90.6250	9.3750

Gross tonnage				
Accident type	1	2	3	4
1	36.1702	23.4043	29.7872	10.6383

2	18.3674	48.9796	28.5714	4.0816
3	36.3636	18.1818	36.3636	9.0909
4	46.6667	26.6667	20.0000	6.6667
5	62.9630	18.5185	7.4074	11.1111
6	19.2308	38.4615	38.4615	3.8462
7	75.0000	8.3333	8.3333	8.3333
8	52.1739	26.0870	13.0435	8.6957
9	38.2353	29.4118	20.5882	11.7647

Hull type				
Accident type	1	2	4	5
1	72.3404	10.6383	8.5106	8.5106
2	81.6327	6.1225	4.0816	8.1633
3	45.4545	27.2727	9.0909	18.1818
4	53.3333	33.3333	6.6667	6.6667
5	59.2593	7.4074	11.1111	22.2222
6	76.9231	7.6923	7.6923	7.6923
7	41.6667	25.0000	8.3333	25.0000
8	52.1739	4.3478	4.3478	39.1304
9	67.6471	2.9412	5.8824	23.5294

Information		
Accident type	1	2
1	64.4445	35.5556
2	31.9149	68.0851
3	33.3333	66.6667
4	69.2308	30.7692
5	68.0000	32.0000
6	25.0000	75.0000
7	60.0000	40.0000
8	71.4286	28.5714
9	68.7500	31.2500

Length			
Accident type	1	2	3
1	58.6957	34.7826	6.5217
2	60.4167	37.5000	2.0833
3	50.0000	40.0000	10.0000

4	71.4286	21.4286	7.1429
5	84.6154	7.6923	7.6923
6	52.0000	44.0000	4.0000
7	81.8182	9.0909	9.0909
8	77.2727	18.1818	4.5455
9	63.6364	30.3030	6.0606

Sea condition		
Accident type	1	2
1	55.5556	44.4444
2	31.9149	68.0851
3	66.6667	33.3333
4	61.5385	38.4615
5	24.0000	76.0000
6	54.1667	45.8333
7	40.0000	60.0000
8	47.6191	52.3810
9	59.3750	40.6250

Ship age						
Accident type	1	2	3	4	5	6
1	18.3674	16.3265	8.1633	8.1633	26.5306	22.4490
2	13.7255	13.7255	11.7647	11.7647	45.0980	3.9216
3	15.3846	7.6923	23.0769	7.6923	38.4615	7.6923
4	11.7647	11.7647	17.6471	5.8824	35.2941	17.6471
5	17.2414	10.3448	10.3448	13.7931	34.4828	13.7931
6	21.4286	10.7143	10.7143	14.2857	21.4286	21.4286
7	7.1429	14.2857	21.4286	7.1429	35.7143	14.2857
8	12.0000	12.0000	12.0000	16.0000	24.0000	24.0000
9	13.8889	19.4444	5.5556	11.1111	36.1111	13.8889

Ship operation								
Accident type	1	2	3	4	5	6	7	8
1	1.9608	1.9608	1.9608	5.8824	5.8824	1.9608	78.4314	1.9608
2	18.8679	1.8868	18.8679	11.3207	1.8868	5.6604	39.6226	1.8868
3	6.6667	6.6667	13.3333	6.6667	20.0000	6.6667	33.3333	6.6667
4	5.2632	10.5263	5.2632	5.2632	5.2632	10.5263	52.6316	5.2632
5	29.0323	3.2258	3.2258	16.1290	22.5806	3.2258	16.1290	6.4516

6	10.0000	6.6667	13.3333	16.6667	6.6667	6.6667	33.3333	6.6667
7	18.7500	6.2500	6.2500	6.2500	6.2500	12.5000	37.5000	6.2500
8	7.4074	7.4074	7.4074	11.1111	37.0370	3.7037	22.2222	3.7037
9	18.4210	21.0526	7.8947	13.1579	10.5263	7.8947	18.4210	2.6316

Ship speed		
Accident type	1	2
1	80.0000	20.0000
2	89.3617	10.6383
3	88.8889	11.1111
4	92.3077	7.6923
5	92.0000	8.0000
6	70.8333	29.1667
7	90.0000	10.0000
8	95.2381	4.7619
9	93.7500	6.2500

Time of day		
Accident type	1	2
1	42.2222	57.7778
2	51.0638	48.9362
3	55.5556	44.4444
4	53.8462	46.1538
5	60.0000	40.0000
6	58.3333	41.6667
7	70.0000	30.0000
8	52.3810	47.6191
9	65.6250	34.3750

Vessel condition		
Accident type	1	2
1	84.4445	15.5556
2	68.0851	31.9149
3	77.7778	22.2222
4	53.8462	46.1538
5	60.0000	40.0000
6	79.1667	20.8333
7	20.0000	80.0000

8	80.9524	19.0476
9	62.5000	37.5000

Voyage segment						
Accident type	1	2	3	4	5	6
1	2.0408	12.2449	2.0408	51.0204	30.6123	2.0408
2	1.9608	15.6863	29.4118	39.2157	11.7647	1.9608
3	7.6923	7.6923	7.6923	46.1538	23.0769	7.6923
4	5.8824	5.8824	17.6471	52.9412	11.7647	5.8824
5	13.7931	17.2414	3.4483	44.8276	17.2414	3.4483
6	7.1429	10.7143	42.8571	10.7143	14.2857	14.2857
7	7.1429	7.1429	21.4286	28.5714	28.5714	7.1429
8	8.0000	4.0000	8.0000	60.0000	8.0000	12.0000
9	19.4444	5.5556	22.2222	36.1111	13.8889	2.7778

Weather condition		
Accident type	1	2
1	66.6667	33.3333
2	46.8085	53.1915
3	44.4444	55.5556
4	61.5385	38.4615
5	60.0000	40.0000
6	62.5000	37.5000
7	60.0000	40.0000
8	66.6667	33.3333
9	65.6250	34.3750

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