**Jiang, M, Lu, J, Yang, Z and Li, J**

**Risk analysis of maritime accidents along the main route of the Maritime Silk Road: a Bayesian network approach**

# Risk analysis of maritime accidents along the main route of the Maritime Silk Road: a Bayesian network approach

**Abstract:** The safety of maritime transportation along the 21st century Maritime Silk Road (MSR) is important to ensure its development and sustainability. Maritime transportation poses risks of accidents that can cause the death or injury of crew members and damage to ships and the environment. This paper proposes a Bayesian network (BN) based risk analysis approach that is newly applied in the main route of the MSR to analyse its relevant maritime accidents. The risk data are manually collected from the reports of the accident that occurred along the MSR. Next, the risk factors are identified and the results from the modelling method can provide useful insights for accident prevention. Historical data collected from accident reports are used to estimate the prior probabilities of the identified risk factors influencing the occurrence of maritime accidents. The results show that the main influencing factors are the type and location of an accident and the type, speed and age of the involved ship(s). In addition, scenario analysis is conducted to analyse the risks of different ships in various navigational environments. The findings can be used to analyse the probability of each possible maritime accident along MSR and to provide useful insights for shipowners' accident prevention.

**Keywords:** Maritime Silk Road, maritime risk, maritime safety, Bayesian network, sensitivity analysis, scenario analysis

## 1. Introduction

More than 90% of international trade is achieved by the movements of seaborne cargoes due to the capability of ships in providing low-cost and efficient transportation (Valentine 2015). The 21st Century Maritime Silk Road (MSR), proposed by China in 2013, is a new type of trade corridor connecting China to the world following newly developed global political and trade patterns. At present, 80% of China's oil imports, 50% of natural gas and 42.6% of other seaborne cargoes' goods are transported through the MSR (Jiang et al. 2018). Clearly, along with the development of the 21st Century MSR, the demand for shipping transportation and international logistics is significantly increased. This increase results in heavier traffic along the corridor, which in return causes higher navigational safety and security concerns. Serious maritime accidents could cause casualties, economic loss, environmental pollution and traffic congestion and further affect trading cost and volume (Zhang et al. 2013). Despite the massive investment to improve the infrastructure construction and development of the MSR in the past years, we have seen a large number of safety and security accidents occurred along the MSR. On April 22, 2014, a tanker was attacked by pirates in the Straits of

Malacca (IMO, 2018). Approximately 2500 metric tonnes of oil and the crew's personal belongings were stolen, and the master, chief officer and chief engineer were kidnapped by the robbers. On May 9, 2016, a flag of convenience product tanker was hijacked by armed pirates (IMO, 2018). In addition, off the coast of Kochi, India, a bulk carrier collided with a fishing vessel causing the death of two fishermen and bad injures of eleven crew members on June 11, 2017 (IMO, 2018). Managing risks is one of the priorities to ensure the success of the MSR (Wan et al. 2018), and it is therefore crucial to analyse previous accidents to identify important influencing factors and realise rational risk prediction to prevent the reoccurrence of similar accidents along the MSR. The markets of the nations along the MSR have a large consumption potential (Valentine 2015). The transported goods mainly include crude oil, ore and grain (Valentine 2015). Once an accident occurs, it will have an enormous negative impact on global trade. The countries along the MSR are developed at different levels in terms of infrastructure construction, which has an impact on shipping transportation (Lee at al. 2018). Once there is a detention in a certain port, it will cause delays throughout the whole transport supply chain. Therefore, accident prevention is a challenging yet essential task to be addressed.

This paper aims to analyse the characteristics of the maritime accidents that occurred along the MSR (e.g. pirate attacks, ship hijackings and traffic accidents) and to develop a new risk analysis and prediction model based on a data-driven Bayesian network (BN). It includes the following three objectives:

1) Collection of the accident data relating to the MSR from the database of the Marine Casualties and Incidents and Piracy and Armed Robbery reported by the International Maritime Organization (IMO).
2) Identification and analysis of the factors influencing the investigated accidents.
3) Development and validation of a BN-based risk prediction tool for maritime accident prevention along the MSR.

To achieve these objectives, the rest of this paper is organized as follows. Section 2 presents a literature review of maritime accident research and the application of BN in maritime risk analysis and prediction. Section 3 describes the method of data collection and processing to show the navigational safety status of the MSR. The results from Section 3 and the findings from Section 2 jointly address the first objective while highlighting the strong need for and research gap addressed by this study. The methodology of developing a BN-based risk analysis model for the MSR is proposed in Section 4 to address the above objective 2 (i.e. identification of the factors) and objective 3 (i.e. development of the methodology) in part. In Section 5, a sensitivity analysis is conducted to identify the main influential risk factors for addressing objective 2 (i.e. analysis of the risk factors) in full. The scenario analysis is applied to find useful information for maritime stakeholders to make decisions regarding risk reduction and accident prevention for addressing objective 3 (i.e., validation of the model). Section 6 concludes the paper with future research directions.

## 2. Literature review

In this paper, we collected papers on all kinds of aspects of maritime accidents from the academic journals written in English. The key words used to search the papers including maritime accidents, shipping safety/risk, maritime safety/risk. The data sources such as web of science, engineering village and science direct are used to search the papers. 78 papers were found and 52 papers were used in this paper. Then, these papers were categorized depending on aspects such as the main concerns, accident types, accident locations, major causes, methods and data sources. The key words included maritime accident, maritime risk, risk analysis and safety.

### *2.1. Studies of maritime accidents*

Previous studies of maritime accidents refer to both safety and security risks, involving pirate attacks (Pristrom et al. 2013; Yang et al. 2013), ship hijackings (Pristrom et al. 2016), collision (Wu et al. 2019), grounding (Uğurlu et al. 2016), contact, and so on (Mullai and Paulsson 2011). The studied locations of maritime accidents include Western or Eastern Indian Ocean (Pristrom et al. 2016), Arctic waters (Baksh et al. 2018), Norwegian waters (Størkersen 2017), Baltic Sea and Gulf of Finland (Mullai and Paulsson 2011), Greece (Nævestad et al. 2019), the UK (Akhtar and Utne 2014), Turkish Straits (Uğurlu et al. 2016) and China's Yangtze River (Zhang et al. 2013; Wu et al. 2015; Wang et al. 2019). Maritime accidents at sea, in waterways and/or ports have been systematically analysed during the past 50 years (Luo and Shin 2016).

The causes of maritime accidents mainly include environmental effects, human factors, and ship conditions, or a combination of these factors (Luo and Shin 2016; Wu et al. 2017; Wang et al. 2018). Regarding environmental effects, previous papers consider the natural or oceanographic environment to be one of the influencing factors that affect maritime accidents. The environmental conditions (i.e., visibility, wind, light, sea, precipitation) and time are recorded when an accident occurs (Mullai and Paulsson 2011). Raiyan et al. (2017) used an event tree with a quantitative analysis to recognize how a single factor, when coupled or not with other factors, was likely to lead to an accident, and the results showed that the ratio of success in avoiding an accident was largely influenced by the visibility in both good and bad weather conditions. Knapp et al. (2011) applied econometric models to measure the effect of significant wave height and wind strength on the probability of casualties and tested whether these effects caused any change. The results showed that although a seasonal pattern existed in the probability of casualties, especially during the winter time, the effect of wind strength and significant wave height did not follow the same seasonal pattern. Weng and Yang (2015) investigated whether the location of an accident affected mortality and found that the accidents that occurred far away from coastal areas typically resulted in higher mortality.

Human factors are seen in many risk analysis studies in the maritime domain, and some human factor analysis models, such as the Human Factors Analysis and Classification System (HFACS), the Technique for Retrospective and Predictive Analysis of Cognitive Errors (TRACEr) and Accident Analyse Mapping (AcciMap), have been widely used. Uğurlu (2018) applied HFACS-PV to analyse human factors in passenger vessel accidents. Akyuz (2015) used the AcciMap and Analytical Network Process (ANP) methods to analyse the causes of marine accidents. The results showed that decision error as a human factor was one of the main contributory factors influencing marine accidents, especially the grounding of ships at sea. Sotiralis et al. (2016) presented an approach based on TRACEr and BN that incorporated human factor considerations into the quantitative risk analysis of ship operations. However, non-traditional security threats, such as pirate attacks and terrorism, have also to be considered. Pristrom et al. (2016) proposed an analytical model that incorporated BN to assess piracy and robbery. Analysis of the above studies helps investigate the influential factors in this study.

In terms of ship conditions, Mullai and Paulsson (2011) considered a ship's properties (i.e., flag, age and ship type) to design a conceptual model for the analysis of marine accidents. Pristrom et al. (2016) proposed a model that took into account the characteristics of a ship (i.e., ship speed and ship type) and environmental conditions to analyse maritime piracy and robbery related incidents.

### *2.2. Risk analysis models*

In terms of maritime accident risk analysis, the IMO proposed a structured and systematic framework called formal safety assessment (FSA). The FSA was introduced as a process to evaluate risks and to provide a decision-making basis for maritime stakeholders. Mentes et al. (2015) proposed an FSA-based integrated methodology to identify and evaluate driving factors such as geographical locations and failure modes causing fatality for cargo ships. Furthermore, the authors also developed a risk analysis method to make maritime transport cleaner and safer. Although it is widely used (Wang et al. 2019; Mentes et al. 2015), FSA has some drawbacks, such as the inability to accurately quantify risks and the lack of reliability and effectiveness (Yang et al. 2013), when subjective knowledge is used in the absence of historical data.

Advanced methods have been introduced to calculate the quantitative causal relationship between maritime risks and their influencing factors, including fuzzy logics, evidential reasoning and BNs. Although fuzzy logic and evidential reason (as well as their combination) have been widely used to deal with fuzziness and incompleteness in maritime risk data (e.g. Yang et al., 2009; Yang et al., 2013), they fail to model the causal relationship among the risk influential factors, for which BN shows its superiority. Having said that, it is revealed that the three main uncertainty treatment methods are often used in a combined way together with other traditional risk analysis methods such as Fault Tree Analysis (FTA). Kum and Sahin (2015) applied fuzzy FTA to investigate marine accidents and incidents and to reveal their causes via root cause analysis. For instance, Zhang et al. (2013) used the FSA concept and a BN technique to estimate the navigational risk of the Yangtze River, and undertake the scenario analysis based on the risk model that considered both the probability and consequences of accidents to demonstrate the application of the proposed model. Zhou et al. (2018) proposed a fuzzy and Bayesian network CREAM model to analyse human reliability and to control the risk level caused by human factors. Yang et al (2019) present a novel approach for combining evidential reasoning with BN to facilitate human reliability analysis. Moreover, fuzzy evidential reasoning approach has been applied in the CREAM model to overcome the problem of ignoring the uncertainty exists in practice (Wu et al. 2017). Zhang (2014) discussed that fuzzy logic, evidential reasoning and BNs can address some hindrances to maritime risk assessments. These methods can facilitate risk assessment with uncertainties using objective data and subjective knowledge (e.g. Wu et al. 2019; Wu et al. 2018; Yang et al. 2019; Li et al. 2014).. However, in this study, BN is favoured due to its advantages of modelling the dependency between different influential factors and between the factors and the investigated risk types (Baksh et al. 2018).

### *2.3. Applications of BN in maritime risk analysis*

BNs have been widely used in the risk analysis of maritime accidents because of their advantages, including forward (or predictive) analysis and backward (diagnostic) analysis. A BN can reflect the dependencies among variables, update the network with new evidence without changing the old network, handle uncertainties, and integrate historical data, related faults and expert knowledge (Baksh et al. 2018). BNs combine prior knowledge and historical data and are considered as a powerful tool for reasoning prediction and error diagnosis in an uncertain environment. Therefore, BNs enable complex risk analysis involving various influencing factors. Wang and Yang (2018) developed a novel risk analysis approach based on BNs to analyse accident severity in waterborne transportation. Bouejla et al. (2014) proposed an innovative solution, with a BN, to managing the risks of maritime piracy against offshore oil fields from the perspective of an entire processing chain.

The first step to establish a BN for the risk analysis of maritime accidents is structure learning. Generally, the structure of a BN can be determined with the help of expert knowledge, literature review, data learning, or a combination of them. Bouejla et al. (2014) built their BN structure based on the database from the IMO and qualitative knowledge offered by experts in the maritime domain. Pristrom et al. (2016) used the data collected from the Global Integrated Shipping Information System (GISIS) together with six expert judgements, which were collected and weighted to estimate the likelihood of a ship being hijacked in the Western Indian or Eastern African region.

In addition, the structure of the BN can be learned via a machine learning algorithm, but in this method, the problems of generating unreasonable and ambiguous relationships may occur. To avoid this phenomenon, previous studies had combined data-driven machine learning algorithms with expert knowledge to verify the final structure and to rationalize the meaning of the relationship. Zhang et al. (2013) estimated the navigational risk of the Yangtze River using a BN technique. The BN structure, called the preliminary BN, was first learned from data, and then parameter sensitivity analysis was used to justify the dependencies of the nodes. If any negative feedback occurred, the appropriate modification would be made. Cooper and Herskovits (1992) presented a Bayesian method realised by a K2 algorithm for constructing BN structure from database. Akhtar and Utne (2014) proposed a BN for modelling the risk of maritime ship accidents. Data were first collected to develop a BN structure and the associated conditional probabilities. However, due to the lack of data, expert judgement was required; then, the qualitative model and its taxonomy were developed for structure learning.

In summary, this study conducts a pioneering experimental study by using the BN to analyse the risk of maritime accidents along the MSR. The probabilities of maritime accidents on the MSR are quantified using the BN based on the influencing factors and their associated probabilities. The methodology relies on historical data and a data-driven machine algorithm in the process of building a BN. The main aim is to use the BN risk model to predict the risk consequence in maritime accidents along the MSR.

## 3. Data collection and processing

The main route of the 21st century MSR starts from Quanzhou, passes through Fuzhou, Haikou, Beihai, Henei, Kuala Lumpur, Jakarta, Colombo, Kolkata, Nairobi and Athens and finally arrives in Venice.

This paper conducts a statistical analysis of the accidents that occurred from 2010 to 2017 to effectively and comprehensively identify the main risk factors of the MSR. A total of 413 marine accidents, including detailed reports from the IMO, with the ship specification data from Lloyd’s Register Fairplay (LRF), were collected. The data from the IMO contains two kinds of information. The first category of information is about factual data collected from various sources and the second category is about more elaborated information based on the reports of accident investigations. Using these two kinds of information, this paper extracted the influencing risk factors referring to previous literature, expertise and available experience (e.g. Zhang et al. 2013; Wang et al. 2018; Baksh et al. 2018).Table 1 shows the data sources used to build the dataset. As the databases used different classifications of accidents, they were manually reclassified for their compatibility with the definitions developed by the IMO for three categories: very serious, serious, and less serious. With respect to seriousness, the definitions developed by the IMO and given in MSC-MEPC.3/Circ.1 were used (See Table 2).

In this paper, the accident types include collision, pirate attacks, ship hijackings, contact, stranding, and other non-classified types in accordance with IMO (IMO. 2018). A collision refers to the situation in which two or more ships hit each other in a relatively short time. A pirate attack is defined as a situation in which a ship is attacked by robbers, typically with the goal of stealing cargo and other valuable items or properties. A ship hijacking refers to a situation in which a ship is hijacked by armed robbers using criminal violence, with the goal of hijacking ships and crews for ransom. A contact is defined as a situation in which a ship is struck by any fixed or floating objects. A stranding refers to the situation in which a ship strikes an object on the sea floor, or strikes or touches the bottom.

According to the local time of sunrise and sunset, the time of the accident was defined as two categories: daytime and night-time (Pristrom et al. 2016). The natural environment data (i.e., fog, visibility, rain, wind) used in this study were collected from Remote Sensing Systems (RSS). RSS is a scientific research company engaged in processing and analysing microwave data from satellites. The data are rich with information about rain rates, cloud cover, wind speeds, etc. In this study, the RSS dataset that provides the wind speed, visibility and rain rate was added to the casualty data at the same time. The available experience such as Beaufort Wind Scale, Fog and Visibility Scale, and Classification Standard of Rainfall by China Meteorological Administration were used to define the states. The previous studies that mentioned the calculation of the states of risk factors can provide a reference to determine the optimum number of states (e.g. Wang et al. 2018).The states of ship type, accident location and ship flag were derived from the database of the IMO and LRF (Knapp et al. 2011; Weng and Yang 2015), while the investigation reports recorded in detail the states of ships (i.e., ship speed, ship type, ship age, ship flag, ship flow and location) at the time of the accidents. The unique IMO number of the ships is used to combine information from different databases to ensure the consistency of the input data in this study. In addition, the investigation reports with detailed information were applied to help better understand the progress of the accident (Akhtar and Utne 2014; Wang et al. 2018; Yang et al. 2019).

Table 1 Data sources used for the dataset.

| Data type | Data source |
|---|---|
| Casualty data | Lloyd's Register Fairplay (LRF)<br>International Maritime Organization (IMO) |
| Ship characteristics | LRF, IMO, and investigation reports |
| Natural environment | Remote Sensing Systems |

Table 2 The definition of three categories of accidents

| Categories | Definition |
|---|---|
| Very serious | Very serious casualties are the casualties to ships that involve total loss of the ship, loss of life, or severe pollution |
| Serious | Serious casualties are the casualties to ships that do not qualify as very serious casualties and involve a fire, explosion, collision, grounding, contact, heavy weather damage, ice damage, hull cracking, or a suspected hull defect, etc., resulting in immobilization of main engines, extensive accommodation damage, severe structural damage, pollution and/or a breakdown necessitating towage or shore assistance |
| Less serious | Less serious casualties are the casualties to ships that do not qualify as very serious casualties or serious casualties and for the purpose of recording useful information, also include marine incidents which themselves include hazardous incidents and near misses |

Table 3 The statistical and processing results of the risk factors

| Factor | Description | states |
|---|---|---|
| Ship speed (knots) | 5 or less, 5-10, greater than 10 | s1, s2, s3 |
| Ship type | Container ship, bulk carrier, tanker or chemical ship, passenger ship, other | s1, s2, s3, s4, s5 |
| Ship age (years) | 0-5, 6-10, 11-15, 16-20, more than 20 | s1, s2, s3, s4, s5 |
| Ship flag | China, FOC, other | s1, s2, s3 |

| | | |
|---|---|---|
| Location | Port, coastal waterway, sea | s1, s2, s3 |
| Accident type | Collision, pirate, ship hijacked, contact, stranding, other | s1, s2, s3, s4, s5, s6 |
| Fog | No fog or unmentioned, fog | s1, s2 |
| Visibility (km) | 2 or less, 2-10, greater than 10 | s1, s2, s3 |
| Rain | No rain or unmentioned, rain | s1, s2 |
| Wind (m/s) | 0-4,4-7, greater than 7 | s1, s2, s3 |
| Natural environment | Good, poor | s1, s2 |
| Ship flow | Congestion, normal or unmentioned | s1, s2 |
| Traffic environment | Good, poor | s1, s2 |
| Time of day | Daytime, night-time | s1, s2 |
| Accident risk | Very serious, serious, less serious | s1, s2, s3 |

# 4. Methodology

## *4.1. Bayesian network*

A BN (Ghahramani 1998) is a probabilistic graphical model that includes a set of nodes and directed edges that connect these nodes contained in a directed acyclic graph. (DAG). A DAG is a pair $G=(V,E)$, where $V$ is a set of nodes and $E$ is a set of directed edges. The nodes represent random variables, and the directed edges represent the mutual relationship between the nodes, pointing from the parent node to their child nodes. The conditional probability is used to express the relationship strength. The root nodes without a parent node use the prior probability to express the information.

The BN was first introduced by Pearl (1988) in 1985. A BN can handle incomplete data and infer reasoning from uncertain knowledge or information (Wang et al. 2018). The BN has proven to be a powerful tool for uncertain knowledge representation and reasoning and has been widely used in a variety of problems, such as scenario analysis, probability prediction, fault diagnosis, decision making and data updating (Canbulat et al. 2019; Li et al. 2014; Zhang et al. 2013; Bouejla et al. 2014; Sun and Sun 2015 ).

The conditional independence and joint probability distribution are the basic rules of the BN and can be expressed by formulas (1) and (2):

$$P(V_1,V_2,\cdots,V_k / v)=\prod_1^k P(V / v)(i=1,2...k) \tag{1}$$

$$P(V_1,V_2,\cdots,V_k)=\prod_1^k P(V_i / Parent(V_i))(i=1,2...k) \tag{2}$$

where $V_i$ represents the variable, k is the number of the variables, $P(V_1,V_2,\cdots,V_k / v)$ is the conditional probability function, $P(V_1,V_2,\cdots,V_k)$ is the joint probability function, $Parent(V_i)$ represents the parent nodes of $V_i$.

The development of a BN model includes structure learning, parameter learning, and sensitivity analysis and model validation.

### *4.2. BN structure learning*

The expert knowledge and data learning are two main methods to learn a BN structure (Wang et al. 2018). However, the large diversity of expert knowledge cannot guarantee objectivity and accuracy, and it is difficult to realize when the number of nodes is large. Many papers have proposed new methods to search Bayesian structures from data, among which the most common one is the scoring search method. Cooper and Herskovits (1992) proposed the K2 algorithm based on a scoring function and a climbing method. The algorithm calculates the score value of each point in the given order of input nodes. Given the maximum number of parent nodes, it is to select the node with the highest score or a combination of nodes as the parent of the point. However, it will become difficult to search when the order among the nodes is unknown. Therefore, the improved K2 algorithm was applied to realize the structure learning in this paper (Li and Su. 2017). Because the random node ordering tends to lead to poor results, four nodes' input strategies were designed.

The four strategies of the order of nodes are listed as follows:

1) Select node order randomly for comparison.

2) The information gain method was used to calculate the value of each node. After 10-fold cross-validation, the value of each node was arranged in order from the largest to the smallest, and the corresponding number was the input sequence.

3) The values of the nodes were calculated by the chi-square test method, and the values were arranged in order from the largest to the smallest after 10-fold cross-validation, and the corresponding numbers were input in the order.

4) For each node, all nodes except it are traversed, and the node or node combination represented by the maximum value is selected as the parent node of that node.

Information gain and chi-square test methods are effective to measure the importance of each nodes (Li and Su 2017). The chi-square test assigns weight to each node, and quantifies the correlation between nodes. The stronger the correlation is, the higher the score. The information gain method measures how much information nodes bring to the network. The more important nodes bring more information.

The optimal network structure results that is obtained by a scoring function for the four node order input strategies are shown in Figure1.

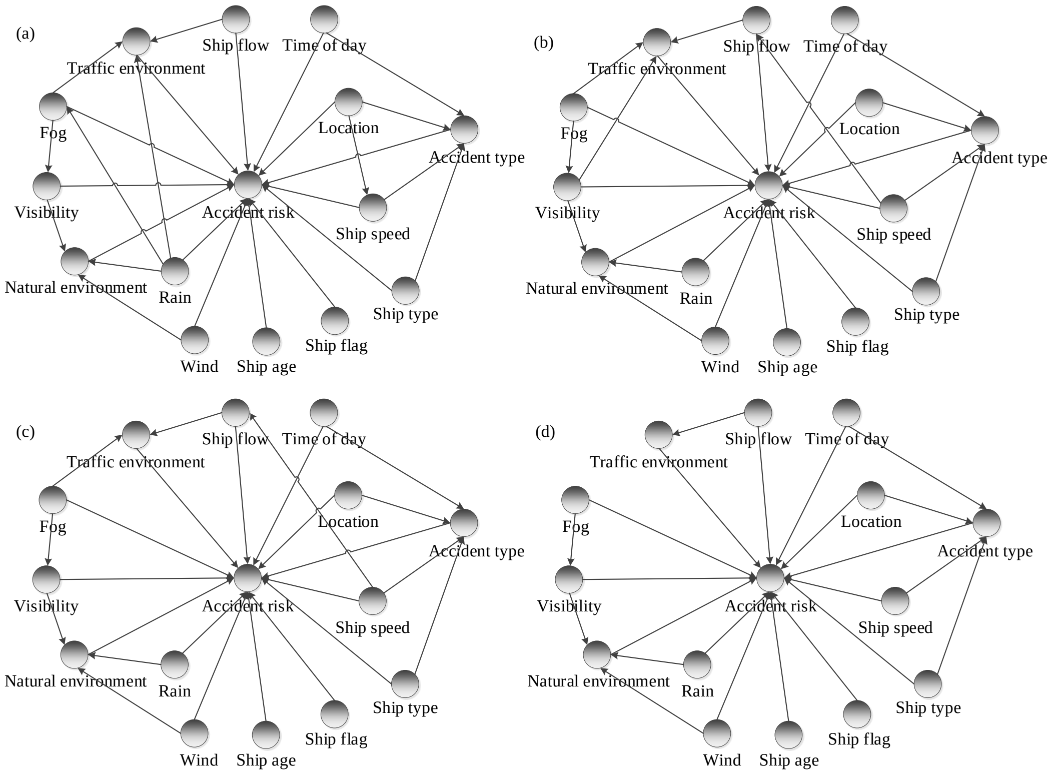


Figure 1. The results of the BN structure for four input strategies

All the four models will be further evaluated in Section 4.4. to test their robustness in this this study.

### *4.3. BN parameter learning*

The causal relationships among the variables are embodied in the BN. Therefore, the conditional probability table (CPT) of each node, that is the states of the child nodes and the input values of parent nodes, must be determined. First, the prior evidence is incorporated into the directed graph; then, the prior information is updated by calculating the posterior probabilities. In addition, the backward analysis can be used to analyse the influencing factors.

The most popular optimization method for learning the parameters of the BN from partially observed data is the expectation-maximization (EM) algorithm (Ghahramani 1998; Wang et al. 2018). In this paper, some observation data such as ship speed at the time of the accident are sometimes not recorded in the IMO investigation report and/or LRF database. The EM algorithm addresses the incomplete data problem by selecting an initial set of parameters. We can apply inference to complete the data through the initial parameter set, or conversely, we can estimate the set of parameters using maximum likelihood estimation through complete data. The EM algorithm iterates two steps until convergence. The two iterates of the EM algorithm are named E-step and M-step (Ghahramani 1998).

E step: Let $\theta^t$ be the known estimated value of the current parameter and let X be the observed data. The E-step computes the expectation of the complete data Z=(X,

Y) via the log-likelihood function of $\theta$. The expectation of the logarithmic likelihood function is defined as:

$$Q(\theta,\theta^t) = E[\log p(X,Y|\theta)|X,\theta^t] \tag{3}$$

M step: To maximize the value $Q(\theta,\theta^t)$, the value of $\theta$ is defined as:

$$\theta = \arg\max_{\theta} Q(\theta,\theta^t) \tag{4}$$

### *4.4. Model evaluation*

To verify the accuracy and reliability of the BN model, a training dataset and testing dataset are assigned randomly from a dataset (Sun and Sun 2015). The overall accuracy (OA) metric in Eq. (5) is a simple and effective indicator of classification model accuracy. It has also been applied in the accuracy evaluation of risk prediction models (Sun and Sun 2015).

This paper also uses precision (i.e. Eq. (6)) and recall (i.e. Eq. (7)) to evaluate the effective detection ability for only one level of risk. However, the precision and recall are mutually restrictive. The F-measure in Eq. (8), which is an average reconciliation index, is adopted to represent the ability of a model to detect high-risk incidents. The above metrics listed in Eq. (5) to Eq. (8) are based on the confusion matrix, as shown in Tables 4 and 5. $T_P$ represents a positive sample predicted positive by the model, while $T_N$ represents a negative sample predicted negative by the model. $F_P$ refers to a negative sample predicted positive by the model, while $F_N$ refers a positive sample predicted negative by the model.

$$overall\ accuracy = \frac{T_P + T_N}{T_P + F_P + F_N + T_N} \tag{5}$$

$$precision = T_P / (T_P + F_P) \tag{6}$$

$$recall = T_P / (T_P + F_N) \tag{7}$$

$$F - measure = \frac{2 * precision * recall}{precison + recall} \tag{8}$$

Table 4 Meaning of the parameters of the evaluation index

| | Predicted positive | Predicted negative |
|---|---|---|
| Real positive | $T_P$ | $F_N$ |
| Real negative | $F_P$ | $T_N$ |

Table 5 Confusion matrix

| | Predicted high risk | Predicted medium risk | Predicted low risk |
|---|---|---|---|
| Real high risk | $T_{highrisk}$ | $F_{medium}$ | $F_{lowrisk}$ |

| | | | |
|---|---|---|---|
| Real medium risk | $F_{highrisk}$ | $T_{medium}$ | $F_{lowrisk}$ |
| Real low risk | $F_{highrisk}$ | $F_{medium}$ | $T_{lowrisk}$ |

Table 6 Comparisons of the accuracy and reliability of different BN structures

| Structure | OA | Risk level | Precision | Recall | F-measure | AUC |
|---|---|---|---|---|---|---|
| | | High risk | 0.609 | 0.7 | 0.651 | 0.671 |
| Fig. 1. (a) | 0.663 | Medium risk | 0.7 | 0.683 | 0.691 | 0.574 |
| | | Low risk | 0.65 | 0.591 | 0.619 | 0.687 |
| | | High risk | 0.682 | 0.75 | 0.714 | 0.694 |
| Fig. 1. (b) | 0.723 | Medium risk | 0.75 | 0.732 | 0.741 | 0.669 |
| | | Low risk | 0.714 | 0.682 | 0.698 | 0.812 |
| | | High risk | 0.727 | 0.8 | 0.762 | 0.857 |
| Fig. 1. (c) | 0.783 | Medium risk | 0.805 | 0.805 | 0.805 | 0.712 |
| | | Low risk | 0.8 | 0.727 | 0.762 | 0.862 |
| | | High risk | 0.773 | 0.567 | 0.654 | 0.845 |
| Fig. 1. (d) | 0.855 | Medium risk | 0.878 | 0.878 | 0.878 | 0.872 |
| | | Low risk | 0.9 | 0.818 | 0.857 | 0.896 |

In addition, the area under the curve (AUC) of the receiver operating characteristic curve (ROC) is used to estimate the reliability of the model. The ROC is a plot of the sensitivity in Eq. (9) (Y-axis) against a false positive rate, which is equal to 1-specificity in Eq. (10) (X-axis). The AUC is generally between 0.5 and 1, and the larger the value of the AUC is, the better the reliability of the model.

$$sensiivity = T_P / (T_P + F_N) \tag{9}$$

$$specificity = T_N / (T_N + F_P) \tag{10}$$

The evaluation results based on the different structures shown in Figure 1 are shown in Table 6. The evaluation results indicate that the structure in Figure 1 (d) has the best accuracy and reliability. As a result, the structure in Figure 1 (d) was selected in the subsequent analysis.

***4.5. Sensitivity analysis***

Sensitivity analysis is a widely used method to analyse the sensitivity of associated variables to identify the influential factors that can minimize the uncertainty of the target factor (i.e. accident risk), which can be denoted by the degree of reduction in information entropy. All the formulas for sensitivity analysis are calculated with the software package NETICA.

Information entropy is a statistic that describes the degree of dispersion of random variables. When the information entropy increases, the uncertainty of the variable also increases. The calculation formula is described as follows:

$$H(Y) = -\sum_{y \in Y} P(y) \log P(y) \tag{11}$$

where $H(Y)$ is the information entropy of random variable Y, and $P(y)$ is the prior probability of Y.

Mutual information represents the amount of information shared between two variables and is a measure of the degree of interdependence of variables. Mutual information is used to indicate the degree to which the entropy of the query node is reduced given the probability of evidence nodes. The mutual information of two discrete random variables X and Y can be defined as follows:

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

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

## 5. Results

### *5.1. Marginal probability distribution of the BN*

As the node 'accident risk' has 14 parent nodes, its CPT is large. Therefore, a part of the CPT of 'accident risk' is calculated based on the database from the IMO and LRF, and shown in Table 7. Furthermore, the marginal probability distribution of the BN is shown in Figure 2, which aids the explanation of the effects of different influencing factors on maritime accident risk consequence.

The accident type with the highest probability was pirate activity, accounting for 45.36% of all accidents. Therefore, defence measures, such as barbed wire mounted on the bulwark, armed guards or long distance acoustic devices, should be applied in ships according to the ship type analysis. Other anti-piracy measures, such as arranging extra personnel to monitor suspicious vessels or conducting regular anti-piracy exercises, should also be taken into consideration.

Most of the ships involved in accidents were bulk carriers (45.59%), and the most common flag was FOC (48.78%). Ships that were less than 5 years old accounted for the largest percentage (30.49%). Therefore, maritime stakeholders should strengthen the management of bulk carriers and improve their safety at sea. When choosing a ship, the shipper may take the flag and age of the ship as the reference.

In terms of the navigational environment, 55.43% of the accidents occurred under good conditions, and the ship flow was usually normal (68.11%). Under favourable navigation conditions, however, the crew members should still not let their safeguard down, remaining vigilant all the time to ensure the safe navigation of their ships.

Fog related to 17.43% of the accidents, rain was present in 22.63% of the accidents, poor visibility was a factor presented in 16.32% of the accidents, and strong wind counted for 6.65% of the accidents. Thus, the natural environment was usually shown to provide good conditions (58.28%). Moreover, 58.01% of the accidents occurred at night, and 39.92% occurred at a port. Therefore, when the ship is sailing at night, especially berthing in the port or at anchorage at night, the crew members must strengthen the monitoring to ensure the safety of their ships. Table 7 A demonstration of CPT for Accident risk.

| | | | | | | |
|---|---|---|---|---|---|---|
| Traffic environment | s1 | Fog | s1 | Ship flow | s1 | |
| Time of day | s1 | Visibility | s3 | Location | s1 | |
| Natural environment | s1 | Rain | s1 | Ship flag | s1 | |
| Ship speed | s1 | Wind | s1 | Ship age | s1 | |
| Ship type | s1 | | | | | |
| Accident type | s1 | s2 | s3 | s4 | s5 | s6 |
| s1 | 0.258 | 0.177 | 0.723 | 0.018 | 0.001 | 0 |
| s2 | 0.379 | 0.451 | 0.263 | 0.519 | 0.321 | 0.449 |
| s3 | 0.363 | 0.372 | 0.014 | 0.463 | 0.678 | 0.551 |

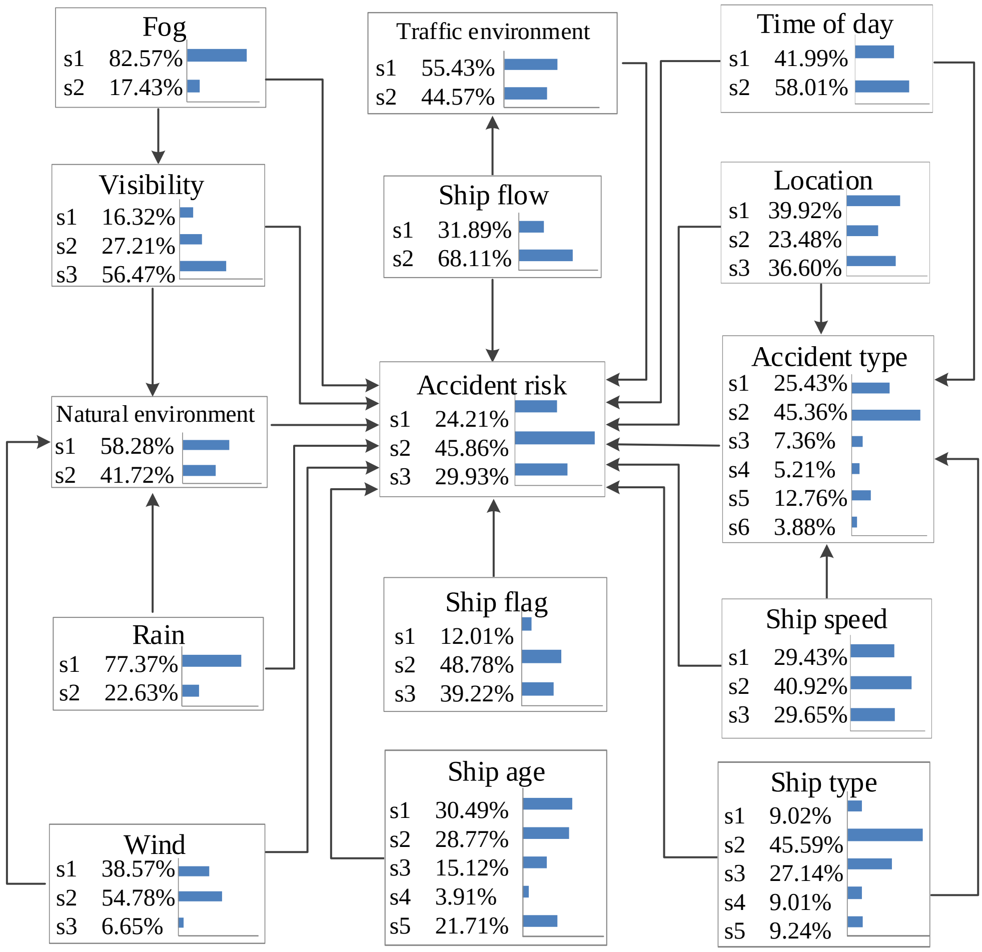


Figure2. Prior distribution of the BN model

### *5.2. Sensitivity analysis*

Sensitivity analysis is a useful way to evaluate factors that make the main contributions to the accident risk. The results of the sensitivity analysis with the software package NETICA are illustrated in Table 8 using mutual information.

According to the mutual information shown in Table 8, the ‘accident risk’ is the target node, and ‘accident type’ has the strongest effect on the target node, with mutual information of 0.1842, followed by ‘location’, with the mutual information of 0.1758. This can also be interpreted as the accident risk having the most sensitivity to the change in the states of the accident type.

Moreover, the variables with mutual information between 0.05 and 0.1, i.e. ‘ship type’, ‘ship speed’, ‘ship age’, ‘ship flag’, ‘time of day’ and ‘ship flow’, also have a significant effect on ‘accident risk’. The remaining variables, i.e. ‘natural environment’, ‘visibility’, ‘wind’, ‘traffic environment’, ‘rain’, and ‘fog’, have relatively weak effects on ‘accident risk’.

Table 8 Mutual information shared with ‘Accident risk’

| Risk variables | Mutual information |
|---|---|

| | |
|---|---|
| Accident type | 0.1842 |
| Location | 0.1758 |
| Ship type | 0.0989 |
| Ship speed | 0.0926 |
| Ship age | 0.0875 |
| Ship flag | 0.0712 |
| Time of day | 0.0681 |
| Ship flow | 0.0514 |
| Natural environment | 0.0378 |
| Visibility | 0.0315 |
| Wind | 0.0121 |
| Traffic environment | 0.0098 |
| Rain | 0.0057 |
| Fog | 0.0018 |

### *5.3. Scenario analysis*

Scenario analysis is an effective and valuable tool of BNs that can construct some useful risk simulations. In the scenario analysis, we can assign evidence in the BN to update the probabilities to generate useful insights. Here, three scenarios are summarized in Table 9 according to the findings from the above sensitivity analysis.

Table 9 Three scenarios of propagation analysis

| Scenario No. | Scenario description |
|---|---|
| 1 | Accident type is set to collision, pirate, ship hijacked, contact and stranding |
| 2 | Location is set to port, coastal waterway and sea |
| 3 | Ship type is set to container ship, bulk carrier, tanker or chemical ship and passenger ship |

Scenario 1 assumes that the accident types are collision, pirate, ship hijacked, contact and stranding. As observed from Figure 3, if the state of ‘accident type’ is collision, the posterior probability of ‘accident risk’ of s1 increases from 24.21% to 61.15%. It indicates that the accident type of collision can increase the severity of accidents. Moreover, the posterior probabilities of the other nodes when the accident type is collision are shown in Figure 4. In addition, if the states of ‘accident type’ are ship hijacked, stranding, pirate, and contact, respectively, the posterior probabilities of the ‘accident risk’ of s1 are 72.15%, 28.14%, 22.71%, and 20.76%, respectively. The results indicate the extent to which the type of accident affects the severity of accidents.

Scenario 2 sets that the locations are port, coastal waterway and sea. As seen from Figure 5, when an accident occurs in port, coastal waterway or at sea, the probabilities of the ‘accident risk’ of s1 are 15.66%, 35.56%, and 47.61%, respectively. The results indicate that when the accident occurred at sea, the severity of the accident is the highest.

Scenario 3 is associated with an observation that we make on the ship type. As seen from Figure 6, the probability of ‘accident risk’ of s1 increases from 24.21% to 43.12% and 35.12%, respectively, when the ‘ship type’ is changed to bulk carriers and tanker/chemical ships. If the states of the ‘ship type’ are, changed to container ships and passenger ships, the probabilities of the ‘accident risk’ of s1 are updated to 16.21% and 17.45%, respectively,. It indicates that bulk carriers, tankers or chemical ships are exposed to high risks.

Based on the above analysis results, we analyse the worst-case scenario by combining the evidence of “hijacked” in accident types, “at sea” in locations, and “bulk carrier” in ship types and present the result in Figure 7. The probability of ‘accident risk’ of s1 increases from 24.21% to 82.93%, indicating a very serious consequence. It should attract safety attention from the involved ship owners and seafarers on-board the involved ships.

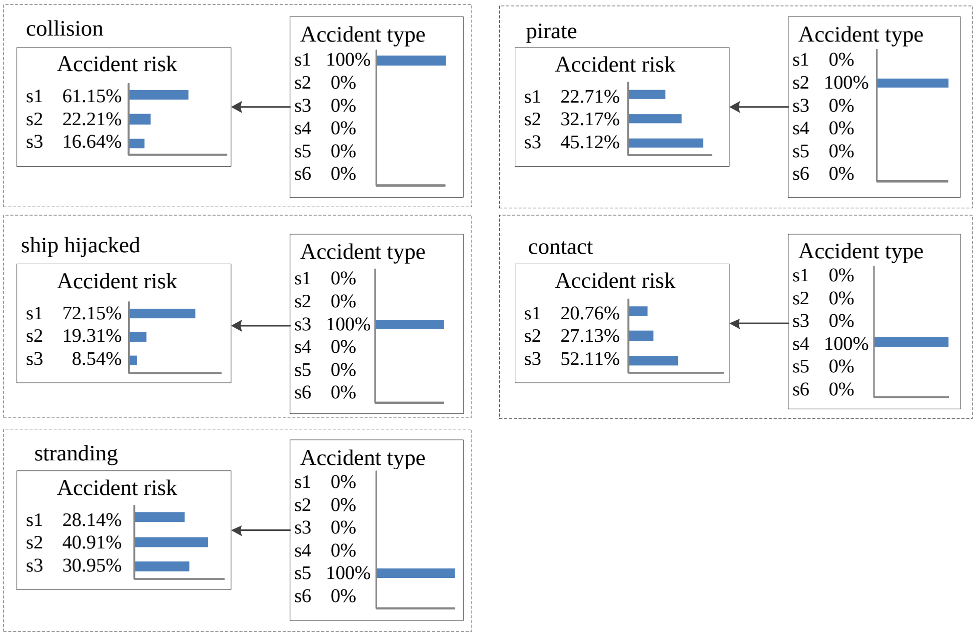


Figure 3. First scenario for different accident types

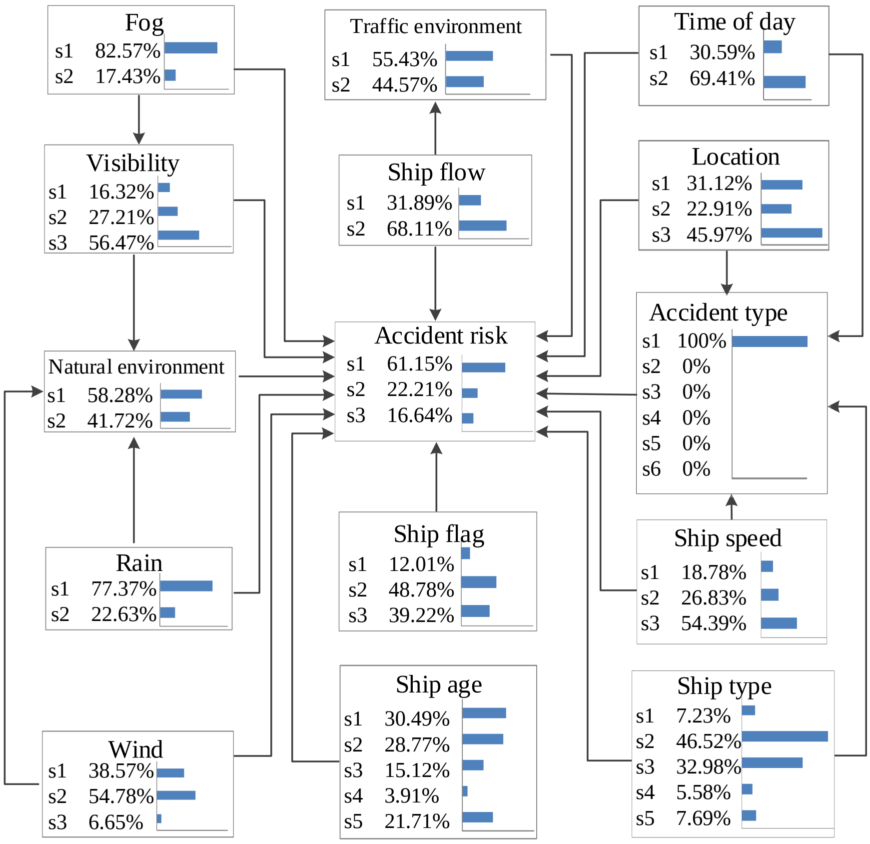


Figure 4 First scenario for collision with detailed statistics

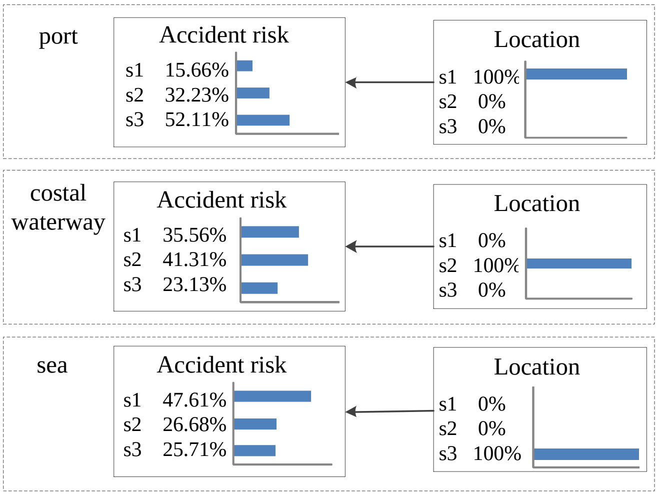


Figure 5. Second scenario for different locations

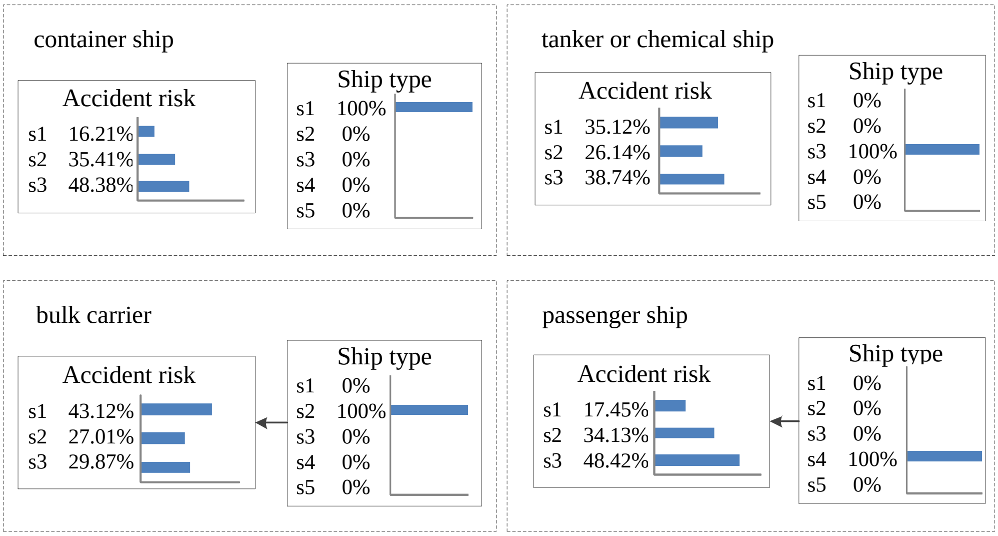


Figure 6. Third scenario for different ship types

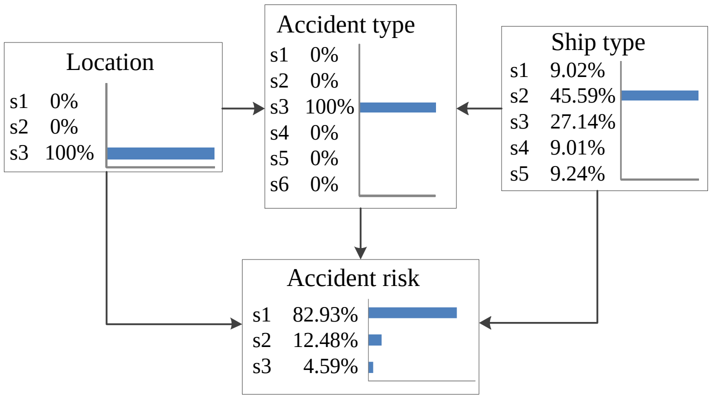


Figure 7. The worst-case scenario by combining the evidence of three nodes

## 6. Conclusion

This study proposes a BN-based risk analysis model for the maritime accidents along the MSR. In this paper, the data were extracted from maritime accident investigation reports and an existing database, and the structure of the BN was learned from the data using the K2 algorithm and was trimmed based on the results of model validation to determine the best structure. The conditional probabilities of the BN were learned by the EM algorithm. The sensitivity analysis based on the mutual information reveals the rank of the impact of various factors influencing maritime accidents. The scenario analysis was conducted based on the sensitivity analysis to assess some potential scenarios. Three different scenarios including different observations were defined for effective safety management and accident prevention. The sensitivity and scenario analysis results show that the accident type has the most significant contribution to accident risk; if the state of the accident type is hijacked, the risk level of the accident risk is the highest; if the state of the accident type is contact, the risk level of the accident risk is the lowest.

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