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An integrated risk assessment model for safe Arctic navigation

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ABSTRACT

Safety is always the first concern for a ship's navigation in the Arctic. Ships navigating in the Arctic may face two main accident scenarios, i.e., getting stuck in the ice and ship-ice collision. More specifically, excessive speed may cause severe hull damage, while a very low speed may lead to a high probability of getting stuck in the ice. Based on this multi-risk perspective, an integrated risk assessment model was proposed to obtain the overall risk using the Bayesian Network (BN), in which the probabilities of accident occurrence and the severities of the possible consequences for ships getting stuck in the ice and for ship-ice collision could be estimated. Then, the voyage data collected from Yong Sheng's Arctic sailing in 2013 were inputted into the integrated risk assessment model to perform a case study. A sensitivity analysis was performed to validate the proposed model and reveal the inherent mechanisms behind these two accidental scenarios. The proposed model can be applied to identify the safe speed for Arctic navigation under various ice conditions, a duty that is traditionally performed by well-trained crew members, but which entails too many uncertainties. The results can, to some extent, provide useful suggestions for navigators. They are imperative in supporting decision-making to shape the Arctic policy and to enhance the safety of Arctic shipping.

1. Introduction

With the increase of Arctic shipping, more merchant ships are planning to navigate in the Arctic waters, especially during the summer season. Safety is one of the biggest concerns when sailing in the ice-covered waters of the Arctic (Lasserre, 2014; Pierre and Olivier, 2015; Zhang et al., 2017, 2020a). According to previous literature and accident reports, Among the list of causes leading to ship hull damage for ice-going ships, getting stuck in the ice and ship-ice collision can be considered as two of the main frequent causes, which are affected by the encountered ice conditions and by the ship's speed (Tunik, 2000; Zhang et al., 2019a,b, 2020c; Fedi et al., 2020;). The event of getting stuck in the ice has been discussed by many researchers. Montewka et al. (2015) proposed two different probabilistic models based on the Bayesian method to explain the relationship between a ship's performance and her encountered ice conditions. One of the models was built to analyze the effect of environmental variables on ship performance, while the other concentrated on how environmental factors and ship performance can affect the occurrence probability that a ship gets stuck in the ice. However, in both proposed models, engine power was assumed to be fixed, and the ship speed changed in relation to encountered ice conditions. These methods may not always properly describe the risk scenarios in actual Arctic navigation (Douglas, 1991). Turnbull

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et al. (2019) proposed a probabilistic prediction model for the event of getting stuck in the ice based on AIS (Automatic Identification System), log data, and ice charts. This model provided a new perspective to estimate the probability of getting stuck in the ice by using the concept of occurrence frequency. However, this model focuses only on a specific ship type, and cannot be applied to other types of ships. Fu et al. (2016) constructed a Bayesian Network (BN) to estimate the occurrence probability that a ship gets stuck in the ice, in which the ship's performance data and experts' consultation were integrated to evaluate conditional probability tables (CPTs). Kubat et al. (2016) evaluated the risk of getting stuck in the ice from an ice compression perspective; their results, estimated by a database, were found compatible with real events. The ship-ice interaction is a complex, nonlinear, and dynamic response process. However, it would be reasonable to consider the ice load applied to a ship as a quasi-static load. Suyuthi et al. (2014) improved the accuracy of the model for estimating the ice load applied to the ship hull, by proposing a three-parameter statistic Weibull's model. Furthermore, the evaluation of the risk of ship-ice collision events has also been extensively investigated. Khan et al. (2018) proposed a dynamic risk prediction model focusing on ship-ice collision events, using an Object-Oriented BN. Besides, the development of a model from the mechanism of ship-ice collision is also an effective method to evaluate the collision risk. Obisesan and Sriramula (2018) developed a comprehensive model to evaluate the risk associated with ship-iceberg collision. In this model, the performance characterization was initially performed to calculate the probability of structural damage in case of ship-iceberg collision; then, a Fault Tree model was proposed to analyze the accident risk. In addition to these two typical types of accidental events (i.e., getting stuck in the ice and ship-ice collision), several risk assessment models have been developed to evaluate the risk of other types of accidental events in ice-covered waters. Kum and Sahin (2015) investigated accident reports from 1993 to 2011, and proposed a Fuzzy Fault Tree (FFT) model to describe the root causes of accidents in the Arctic. Marken et al. (2015) developed a delay risk quantification evaluation model, using the Bow-tie method combined with the fuzzy set theory to demonstrate the model uncertainties. Afenyo et al. (2016, 2019) and Faury and Cariou (2016) discussed oil spills in ice-covered waters using spill process and modelling algorithms.

The mechanisms behind getting stuck in the ice and behind ship-ice collisions are different but connected. Ships sailing at high speed are more likely to collide with ice and cause hull damage. Instead, ships navigating at a relatively low speed may face a higher risk of getting stuck in the ice. In the present study, these two types of risk are analyzed using one risk assessment model. To the best of the authors' knowledge, less research has been reported to discuss both accidental events simultaneously.

This paper is structured as follows. Section 2 introduces the concepts of the proposed risk assessment model. Section 3 describes the model construction methods. Section 4 introduces the procedure of model construction. Section 5 conducts a case study based on the collected data, and validates the model. The model application is illustrated in Section 6. Finally, Section 7 proposes relevant conclusions and future work.

2. Concepts of the proposed risk assessment model

Maritime accidents can happen as a result of various factors, e.g., weather conditions, equipment utilization, route planning, and human factors (Wang et al., 2020). In addition, other factors related to ice can also lead to accidents for ship navigating in the Arctic. Ice-related risks consist mainly of two elements: the risk of getting stuck in the ice, and ship-ice collision risk. When ships get stuck in the ice, the ice pressure on the hull may cause severe consequences including, but not limited to, damage to the hull and loss of maneuverability. In addition, ships' schedule would also be delayed, disrupting the original plan and causing economic loss and potential adverse environmental impacts. In parallel, ship-ice collision is generally considered as the main contributor to ship hull damage for ships navigating in ice-covered waters, and leads to economic and environmental losses (Khan et al., 2020).

Moreover, it is normally assumed that the navigational risk under ice conditions decreases with the reduction of ship speed. This theory may be arbitrary. It is easy to understand that the risk of ship-ice collision will increase as a ship's sailing speed increases (see e.g., Kim and Kim, 2019). However, it is theoretically hard to evaluate the inherent relationship between ship speed and the risk of getting stuck in the ice. It is true that the ship navigating at a very low speed for due caution or poor judgement, is more likely to get stuck in the ice. Thus, the risk assessment for Arctic navigation needs to consider both types of accidents, and the proposed risk concept can be a criterion to identify safe ship speed, as shown in Fig. 1.

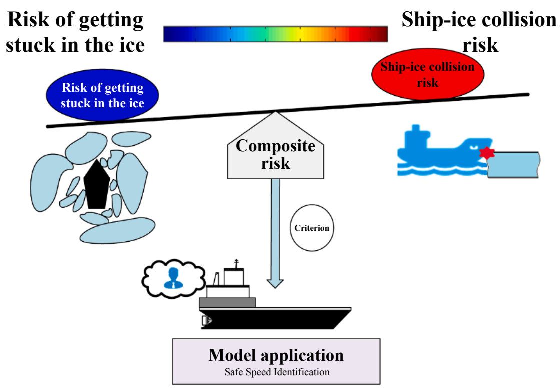

Fig. 1. The framework for risk assessment.

It should be noted that data collection for Arctic shipping is more difficult than for navigation in open waters. Thus, the relative risk assessment needs to be conducted using very limited information. In view of this, the present paper developed a risk assessment model using BN, in which both the objective and subjective probabilities are applied.

The framework of the proposed model can be decomposed into three modules: (1) occurrence probabilities and consequence estimation module; (2) risk assessment module; and (3) model application module. The objective of the first module is to use the BN to evaluate the occurrence probabilities and the consequences of ships getting stuck in the ice and of ship-ice collision, which represent the essential work of risk assessment (Zhang et al., 2020b). The outcomes of this module can be used to estimate the risk in the second module. In the second module, the risk of the two types of accident is discussed in the same standard, based on experts' professional knowledge and using a risk matrix analysis, which provides an effective way for risk assessment. In this way, the quantified risk distribution can be confirmed. In addition, the model validation can be developed to increase the confidence of the proposed model. In the third module, the safe speed in different scenarios can be identified based on the risk assessment model. In this study, it was assumed that ship performance is only affected by ice condition, without any impact from waves or wind. The flowchart of the present study is shown in Fig. 2.

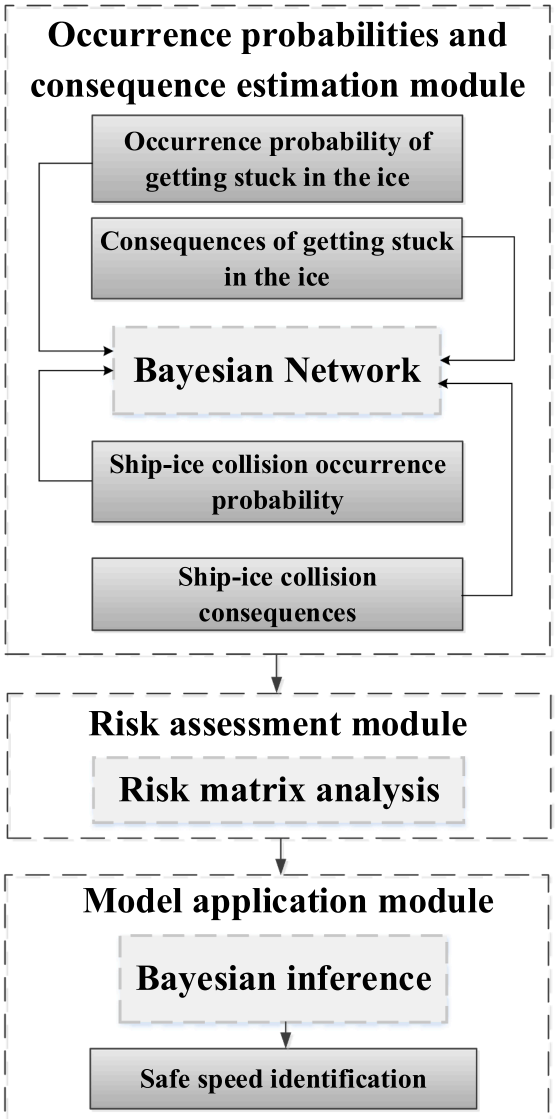

Fig. 2. Flow chart of the present study.

3. Methodologies used in the proposed model

3.1. Bayesian network

The Bayesian Network (BN) is a type of probabilistic graphical-based model, which can be used to describe knowledge uncertainty from objective data and expert opinions. For this reason, BN is a widely used tool in risk analysis.

A BN is a Direct Acyclic Graph (DAG) composed of nodes and directed edges. Every node represents a variable, and edges link these nodes with specific directions. These links can imply the conditional dependency between two variables through the pointing direction, which represents the parent–child relation, with an arrowhead always pointing to a child node. Moreover, if a direct link does not exist between two nodes, then these may be independent or indirectly connected through other nodes.

Each child node has a conditional probability table (CPT) that can imply all the conditional probabilities of all the possible combinations of the states of the parent variables. Nodes with no parent node are often referred to as root nodes. They are not influenced by any other nodes. The CPTs of these root nodes contain respective marginal probability distributions.

The Bayes' theorem is the theoretical foundation of the BN; it is expressed as follows:

$$P(A|E) = \frac{P(A,E)}{P(E)} = \frac{P(A|E)P(A)}{P(E)} \tag{1}$$

where $P(A,E)$ refers to the joint probability of event A and event E; $P(A|E)$ is the posterior occurrence probability of A given an evidence E; $P(A)$ denotes the prior occurrence probability of A, while $P(E)$ refers to the marginal occurrence probability of evidence E; and $P(E|A)$ represents the conditional probability of E given the occurrence of A. The prior occurrence probability $P(A)$ can be calculated by marginalization, utilizing the following equation:

$$P(A) = \sum_{E} P(A,E) \tag{2}$$

The BN enables to update the probability distribution over the possible values of each node, when more information or evidence becomes available. For example, when entering evidence E, this evidence or information will propagate through the network, altering the joint posterior probabilities of event A as follows:

$$P(A_i|E) = \frac{P(E|A_i)P(A_i)}{\sum_j P(E|A_j)P(A_j)} \tag{3}$$

where A_j represents event A in state j; and A_i is the event A in target state I, $\boldsymbol{A} = [A_1, A_2, \ldots, A_n]$.

Entering evidence into the network is a significant part of a probabilistic model. It allows to alter the probabilistic model to a new situation, which contains new posterior probability distributions.

3.2. Risk matrix analysis

Risk can be generally considered as potential of losing something of value. In the present research, risk is understood as the joint effect of occurrence probability and related consequence in a certain risk scenario:

$$R^{\sim}(P, C, S) \tag{4}$$

where R, C, P, and S refer to risk, occurrence probability, related consequence, and scenario, respectively.

The risk matrix is a table that is utilized in risk assessment. It contains various categories of probability or frequency, and several categories of consequence severity. These can be used to define the level of risk, and set priorities in addressing potential hazards. The risk matrix contains grids to map the likelihood or probability of occurrence, and the severity of consequence. The likelihood or probability of occurrence is presented in the rows, while the severity of consequence is presented in the columns. In this way, the risk matrix can increase the visibility of risk distribution and helps decision-making. A typical risk matrix analysis consists of four steps:

(1) Definition of the categories of probability of occurrence and of the consequences of an accident;
(2) Definition of the categories of risk impact;
(3) Establishment of risk-based rules; and
(4) Creation of a graphical depiction of the risk matrix.

Table 1
Classification of accident occurrence probability.

Level	Description
Probable	Occurring once per month (12/year)
Possible	Occurring once per year (1/year)
Remote	Occurring once every 3 years (0.33/year)

Following Afenyo et al. (2017) and Zhang et al. (2013), the criteria to categorize the probability and consequences of an accident in step (1) are shown in Tables 1 and 2. In step (2), the risk levels can be categorized into three groups, namely low (L), medium (M), and high (H) risk. The criteria are described as follows:

Low (L): Accidents that are not critical to people or property, and no further action is required;
Medium (M): Severe accidents that can lead to critical injuries and severe damage to property, requiring the adoption of risk reduction measures;
High (H): Very severe accidents involving the loss of human life and very severe damage to property, requiring the use of as many resources as possible to eliminate the risk.

4. Model construction

4.1. BN nodes

The first step to construct a BN is to identify the factors leading to risk (Fu et al., 2016; Fu et al., 2018a, 2018b; Wan et al., 2019). The final set of nodes identified in our model contains ten main nodes, as shown in Table 3. For the sake of embodying the Arctic navigation risk, the influencing factors of the risk of getting stuck in the ice and of ship-ice collision were analyzed, and the information from these two fields was integrated. The response variables in the current BN model are "risk of getting stuck in the ice", "ship-ice collision risk", and "composite risk".

The identified nodes were discretized into various states. The criteria of discretization were taken from relevant literature and node types. Specifically, the discretization of the state of ice concentration, ice thickness, speed, wave height, wind speed, and wind wave effect were determined following Fu et al. (2016) and Montewka et al. (2015). The states of risk-related nodes, namely getting stuck in the ice, ship-ice collision, consequences of getting stuck in the ice, and consequences of getting stuck in the ice were decomposed in line with Zhang et al. (2013). Three levels of consequence related to these two types of accidents, i.e., "minor", "major", and "critical", were chosen for the sake of model simplification and consistency, also considering experts' knowledge.

4.2. BN model structure

Generally, in a BN the factors are classified as either root causes, intermediate causes, or immediate causes, and are connected by arcs according to the relationship among them (Hänninen et al., 2014). In this way, it is possible to have a better understanding of the hierarchy of factors in a BN. Namely, the factors directly connecting with the top target accidental event are considered as immediate causes; the factors located at the bottom of the BN, with no other factors influencing them, are referred to as root causes; and the factors in the middle position of a BN are considered as intermediate causes.

The environmental factors considered are waves, wind, ice concentration, and ice thickness. As mentioned in Section 2, we assumed that ship performance is only affected by ice condition, without any impact from waves or wind. However, waves and wind exert an influence on ice concentration and thickness, because ice drifting, affected by waves and wind, will change ice distribution and form pressure ice ridges. Therefore, the nodes "ice concentration" and "ice thickness" were set as the child nodes of the node "wind and wave effect".

As for ship performance, the related node is ship speed. During Arctic navigation, especially in ice-covered waters, the speed of a vessel can be significantly influenced by the resistance from the encountered ice conditions. Thus, the node "ship speed" was set as the child node of "ice thickness" and "ice concentration".

It is worth noting that there are four output nodes in the proposed model, namely "getting stuck in the ice", "consequences of getting stuck in the ice", "ship-ice collision", and "ship-ice collision consequences", with "getting stuck in the ice" and "ship-ice collision" directly representing the occurrence probabilities of these two types of accidents. Ship speed, ice concentration, and ice thickness are the factors contributing to the occurrence probabilities of getting stuck in the ice and of ship-ice collision. Moreover, in this paper ship-ice collision denotes the collision between ship and ice, which would cause a certain extent of damage to the ship hull. The occurrence probabilities of getting stuck in the ice and of ship-ice collision are related to similar factors (i.e., ship speed, ice concentration, and ice thickness), but to entirely different theories. For example, ship-ice collisions happen more likely at high ship speeds. On the contrary, in relation to getting stuck in the ice, the contribution is opposite: a low navigation speed increases the occurrence probability of getting stuck in the ice (ENFOTEC et al., 1996). Moreover, the parameters of ice thickness and ice concentration are considered to directly influence the consequences of getting stuck in the ice, because of the ice compression (or pressure). The heavier the ice condition, the more severe the consequences. Moreover, when ships are stuck in the ice, their speed will fall to zero. This reveals that the consequences of getting stuck in the ice are not related to ship speed. As for the consequences of ship-ice

Table 2
Classification of the severity of accident consequences.

Level	Description
Critical	Life threatening injury to at least one person involved in the accident
Major	Extensive damage to the vessel machinery and to other accessories, amounting to more than $10,000
Minor	Minor vessel damage (e.g., scratch) recorded after the accident occurred, with a total damage amounting to less than $10,000

Table 3
BN nodes and states distribution.

Node	State 1	State 2	State 3	State 4
Ice concentration	<50%	50–70%	> 70%	
Ice thickness (cm)	<40	40–80	>80	
Speed (kn)	<5	5–8	8–11	>11
Wave height (m)	<0.5	0.5–1.25	> 1.25	
Wind speed (m/s)	<5.5	5.5–7.9	> 7.9	
Wind wave effect	Severe	Low		
Getting stuck in the ice	Remote	Possible	Probable	
Ship-ice collision	Remote	Possible	Probable	
Consequences of getting stuck in the ice	Minor	Major	Critical	
Ship-ice collision consequences	Minor	Major	Critical	

collision, the contributing factors are ship speed and ice thickness, but not including ice concentration. This is in line with real situations, as ice concentration affects only the occurrence probability of ship-ice collisions.

The BN simulation software GeNIe was used to develop the proposed model (Baksh et al., 2018). The structure of the BN is shown in Fig. 3.

4.3. CPTs estimation

The Conditional Probability Table (CPT) estimation specifies the states of each child node and the input values for the parent nodes in a CPT based on the BN structure, which quantifies the relationships between the variables of the model. Following Fu et al. (2016) and Baksh et al. (2018), the CPT estimation for most nodes can be performed by using multiple sources of data, including objective data and subjective data.

However, the method for CPTs risk-related nodes (i.e., the top three nodes in Fig. 3) is different. Since the CPTs estimation for the nodes “risk of getting stuck in the ice” and “ship-ice collision risk” needs both the occurrence probability and the consequence severity, the risk matrix analysis was utilized, based on the integration of subjective probabilities with expert opinion and relative accidental reports. Moreover, by inputting different data into the BN structure according to demand, different BN quantification models can be obtained.

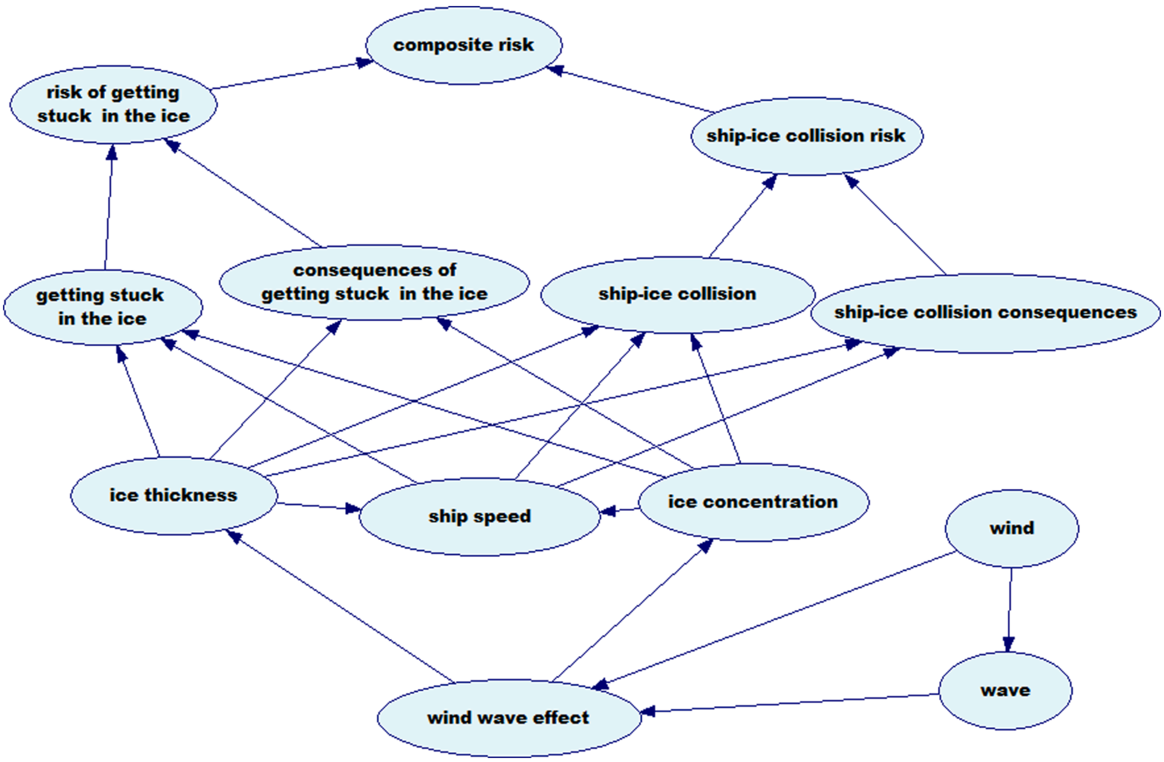

Fig. 3. Structure of the BN model, developed using GeNIe.

5. Case study

A case study based on the records of the vessel "Yong Sheng" was investigated to demonstrate the validity of the proposed risk evaluation model.

5.1. Data sources

The first Chinese merchant ship "Yong Sheng" entered the Arctic area on August 27, 2013 and successfully completed navigation on the September 5, 2013. The voyage that "Yong Sheng" was sailing was taken as the case study voyage of the current paper. Data were collected from several sources including voyage log data, AIS data, ice forecast data, literature, and subjective expert opinion. The log data contains records, meteorological data (wind speed and direction), hydrological data (current speed), and encountered ice concentration data. In parallel, AIS data provided ship's location and speed, while ice thickness data were taken from the forecast data provided daily by the Chinese NMEFC (National Marine Environmental Forecasting Center) during navigation. The portion of data used in the case study is presented in Fig. 4, which contains 179 rows of data uniformly distributed in time (time interval of 1 h), as shown in Fig. 4 (Fu et al., 2016); the vessel parameters are shown in Table 4.

Subjective expert opinions were collected from domain experts such as the captain of the "Yong Sheng", the administration of the China Ocean Shipping (Group) Company (COSCO), and researchers from the Polar Research Institute of China and the Wuhan University of Technology. The multi-source data were integrated into the model constructing process, i.e., CPTs estimation.

5.2. CPTs estimation of case study

In the current study, the probability distribution of the root nodes and the conditional probability distribution of child nodes were estimated by considering objective data (i.e., log data and AIS data) and subjective data (i.e., expert opinions), as discussed above in Section 5.1. However, the estimation method varied for the CPTs of different nodes. For instance, the probability distribution of root nodes such as "wind" and "wave" was obtained simply by calculating the relative frequency of every state of the nodes according to the log data or the AIS data. As for some child nodes such as "ship speed" and "ice concentration", the conditional probabilities were estimated by utilizing the conditional frequency given the state of their parent nodes. However, the objective data have limitations in achieving the CPTs of nodes such as "getting stuck in the ice", "consequences of getting stuck in the ice", "ship-ice collision", and "ship-ice collision consequences" (Fu et al., 2016).

The CPTs of the nodes "getting stuck in the ice" and "ship-ice collision", i.e., their accident occurrence probabilities, were evaluated by integrating expert judgment and available information from literature (Kotovirta et al., 2009; Fu et al., 2016; Turnbull et al., 2019). As for "consequences of getting stuck in the ice" and "ship-ice collision consequences", the former needs to be evaluated from the perspective of ice compression, while the latter was supposed to be measured according to the ice load applied to the ship hull during the accident. Thus, the most convincing estimation of the consequences of getting stuck in the ice and of ship-ice collision should be through full-scale measurement or through physical model test. However, these methods are very expensive, and were excluded from the current model. Instead, to build the CPTs, we collected the historical accident reports, experimental data from existing literature, and expert opinion. The CPTs of the nodes related to risk were estimated using risk matrices; the example of the node "risk of getting stuck in the ice" is shown in Tables 5 and 6. The risk matrix in Table 5, which defines the risk of getting stuck in the ice, was completed by consulting domain experts, which, of course, should obey the fact that a higher occurrence probability or more severe consequence should lead to a higher risk. Then, we transferred this risk matrix to the CPT (Table 6).

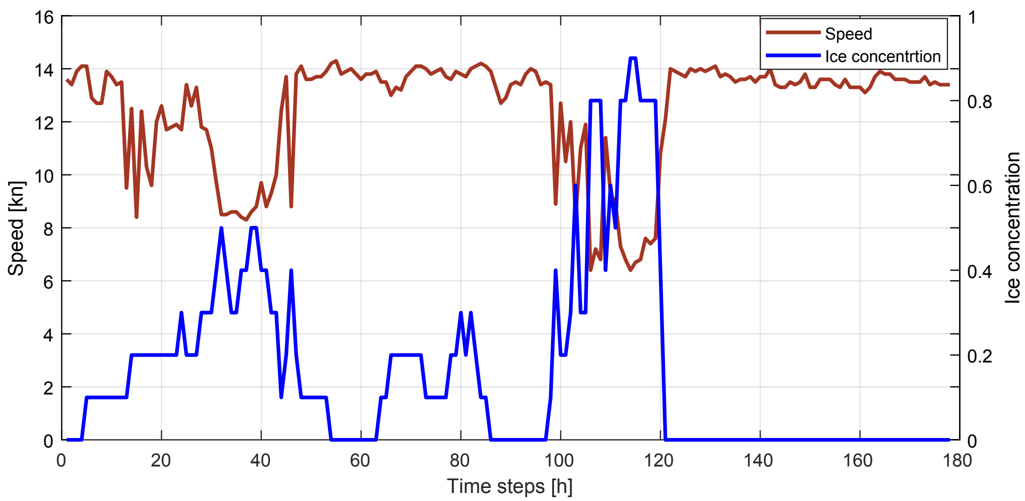

Fig. 4. Portion of the data used in the case study.

Table 4
Characteristics of the vessel "Yong Sheng".

Ship name	Yong Sheng
Type	General cargo
Ice class	PC7
Gross Tonnage (GT)	14,357
Length	155.95 m
Breadth	23.70 m
Draught	8.69 m
Operation power	7074 kW

Source: https://www.coschartering.co.uk/wp-content/uploads/2015/07/MV-Yong-Sheng-passed-Arctic-Waters.pdf.

Table 5
Risk matrix of the risk of getting stuck in the ice.

Probability / Consequence	Remote	Possible	Probable
Critical	High (H)	High (H)	Medium (M)
Major	High (H)	Medium (M)	Medium (M)
Minor	Medium (M)	Medium (M)	Low (L)

Table 6
CPT of the risk of getting stuck in the ice.

Probability	Remote			Possible			Probable		
Consequence	Critical	Major	Minor	Critical	Major	Minor	Critical	Major	Minor
High (H)	1	1	0	1	0	0	0	0	0
Medium (M)	0	0	1	0	1	1	1	1	0
Low (L)	0	0	0	0	0	0	0	0	1

5.3. Results

After evaluating the CPTs by inputting the data into the model, the complete BN can be obtained, as shown in Fig. 5. The occurrence probabilities of the two types of accidents were estimated as mainly 'remote'. The accident occurrence probability could be computed according to the probability distribution. For example, the occurrence probability of getting stuck in the ice was 'remote' (69%), possible (24%), and probable (7%). Thus, the annual number of ships getting stuck in the ice in the Arctic route could be computed as follows:

$$0.69 \times 0.33 + 0.24 \times 1 + 0.07 \times 12 = 1.3$$

According to the statistics from the Northern Sea Route (NSR) information office website, there have been nearly 40 transits through the Arctic route on average every year from 2011 to 2019. Thus, the probability of getting stuck in the ice was:

$$1.3/40 = 0.033$$

This result is in line with Fu et al. (2016) and Montewka et al. (2015). Moreover, from the probability distribution in Fig. 5, we can see that getting stuck in the ice has a lower occurrence probability but more severe consequence, compared to ship-ice collision. Besides, it should be noted that the motivation of this study was not the accuracy of quantitative risk assessment or probability estimation, but to present and validate the proposed methodology on risk evaluation and to provide guidelines, from a risk perspective, on how to make decisions on ship speed adjustment to reduce the navigation risk.

5.4. Model validation

5.4.1. Sensitivity analysis

A sensitivity analysis was performed to validate the proposed model, and to assess the impact of the analyzed factors on the particular target, under a given set of assumptions.

Suppose that B is the target node, whose states are $b_1, b_2, \ldots, b_n$, and that D is the influencing factor, whose states are $d_1, d_2, \ldots, d_n$. Then, the probability of event B with state b_i under given evidence E, i.e., $P(B = b_i \mid E)$, can be expressed using a linear function (Fu

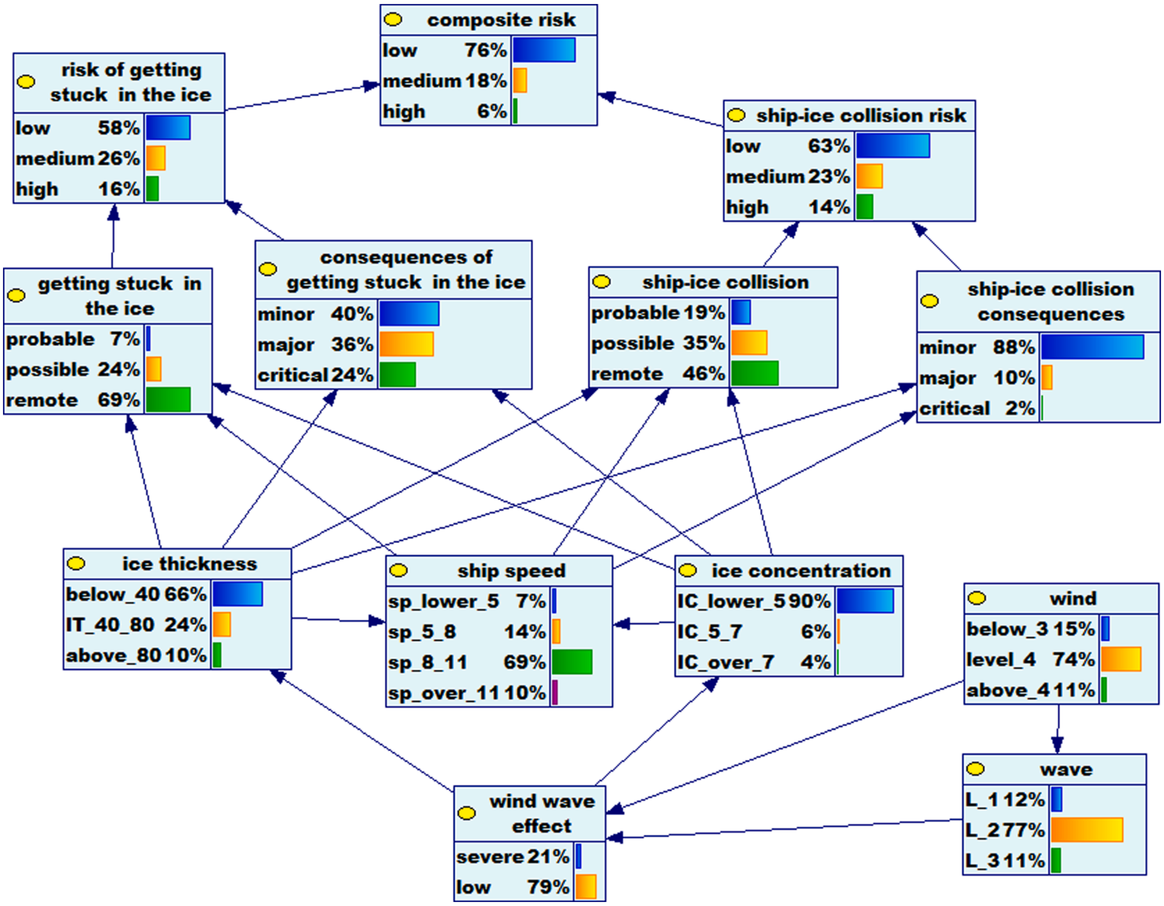

Fig. 5. Risk assessment model for the ship used as case study.

et al., 2016):

$$f(x) = P(B = b_i | E)(x) = \alpha_i \times x + \beta_i \tag{5}$$

where α_i and β_j are the linear function's slope and intercept. Moreover, the sensitivity value of the i-th state of B, with respect to state d of D, could be calculated as follows:

$$S_B = f^{'}(x) = \alpha_i \tag{6}$$

Extending the consideration of a single state b_i, the average sensitivity value of node B with respect to state b of B can be calculated in order to illustrate its overall sensitivity, using the following equation:

$$S_B = \frac{\sum |b_i|}{n} \tag{7}$$

The sensitivity analysis was conducted on the variables "wave", "wind", "ice concentration", "ice thickness", and "ship speed". Any variation in the probability distribution of the chosen nodes was considered in our sensitivity analysis. Taking the event of getting stuck in the ice as an example, we aimed to assess the sensitivity of every chosen variable for the target node "risk of getting stuck in the ice". An increase and a decrease of 10% in probability were performed on the states of each variable, observing the change of the posterior probability of the node "risk of getting stuck in the ice". The results of the example demonstration are shown in Fig. 6, in which the darker red rectangle indicates the nodes with a higher sensitivity.

The purpose of this analysis was to assess which factors can contribute significantly to different accidental events. Thus, the targets set in the analysis were "risk of getting stuck in the ice", "ship-ice collision risk", and "composite risk", respectively. The sensitivity analysis was conducted on these three target nodes, and the sensitivity values were recorded to rank the chosen variables according to the corresponding impact on the target nodes, as shown in Tables 7–9. From the sensitivity analysis, it can be seen that the risk of getting stuck in the ice is more sensitive to ice concentration and thickness, compared to ship speed. The situation is different for the ship-ice collision risk, where the sensitivity of the ship speed was higher than that of ice thickness. The results indicate that the inherent theories for these two types of accidents are different, which is significant for risk control decision-making.

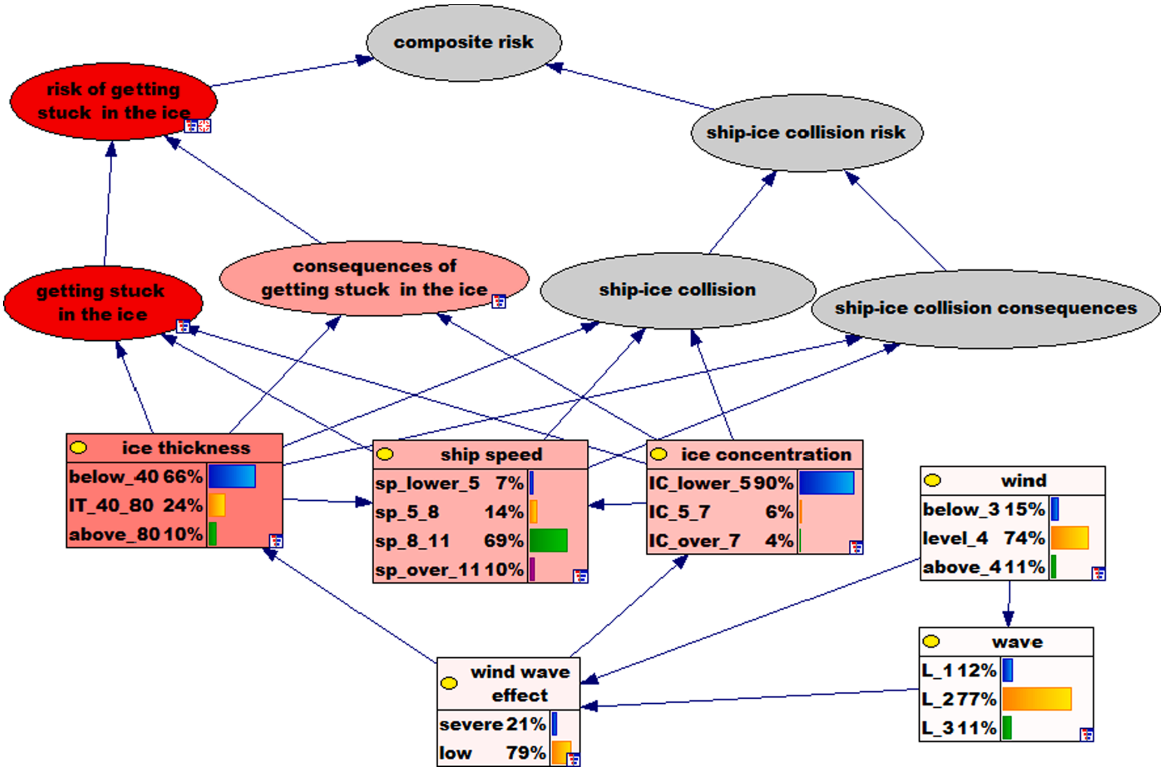

Fig. 6. Sensitivity analysis for the node “risk of getting stuck in the ice”.

Table 7
Sensitivity analysis for the risk of getting stuck in the ice.

Parameter	Average sensitivity value	Rank
Ice thickness	0.11	1
Ice concentration	0.05	2
Ship speed	0.04	3
Waves	0.01	4
Wind	0.01	5

Table 8
Sensitivity analysis for ice collision risk.

Parameter	Average sensitivity value	Rank
Ship speed	0.19	1
Ice thickness	0.12	2
Ice concentration	0.07	3
Waves	0.02	4
Wind	0.01	5

Table 9
Sensitivity analysis for the composite risk.

Parameter	Average sensitivity value	Rank
Ice concentration	0.14	1
Ship speed	0.11	2
Ice thickness	0.07	3
Waves	0.01	4
Wind	0.01	5

5.4.2. Model validation for BN

It should be noted that, although it is arbitrary to consider the validation framework for the BN as a comprehensive analysis to validate the proposed BN model, our framework can raise the confidence to some extent. The validation framework consists of 7 types of conceptual validities: nomological validity, face validity, content validity, concurrent validity, convergent validity, discriminant validity, and predictive validity (Pitchforth and Mengersen, 2013; Goerlandt and Montewka, 2014; Goerlandt et al., 2017). In our research, we concentrated on face, content, and predictive validity because nomological, concurrent, convergent, and discriminant validity require a detailed comparison between the proposed model and other similar models, which currently do not exist. The adequacy of a single type of validation can be discretized into three qualitative categories, namely good, moderate, and defective.

Face validity is a subjective, heuristic judgment of the network variables, structure, and probabilities of the BN. It is the most commonly used type of validity for expert-based BN models, and can assess whether the model can catch the targeted phenomenon. Face validity is conducted by consulting the participating experts about whether the proposed model is the same as what they excepted. In relation to our model, the experts involved in our study come to an agreement about the BN model, with the support of related literature. Therefore, the results of the face validation can be considered as moderate.

The test for content validity can check in detail if the noted variables, and the links between them, are in line with the real system. Moreover, the proposed risk model contains the variables that we think as significant; however, there are many other related variables that are not included in the model, which contribute to the uncertainty of the model. For example, the ice ridges were not included in the model because of the limited data available. In addition, although the state distribution of the selected nodes was discretized according to the available objective and subjective data, there still remains room for the discretization of the nodes in future work. Hence, the adequacy of the content validity was evaluated as moderate.

The last type of validity included in our analysis is predictive validity. In a BN model, predictive validity is usually considered as to contain both the behavior and the output of the proposed model. The qualitative features test and the behavior sensitivity test may be conducted on the BN model to analyze if the proposed model can fit certain criteria. The former aims to compare the behavior of the proposed model output with a qualitative understanding of the expected system output. The later can evaluate how sensitive the target risk node is to small changes in the model variables (see Section 5.4.1). Moreover, conducting sensitivity analysis can also improve the evaluation procedure because, through the sensitivity analysis, the most influential variables can be identified. Therefore, when the experts estimate the parameters of the BN model, they will intend to pay more attention to the more significant variables, which may increase the confidence of the BN model to some extent (Wang, 2006).

6. Discussion

6.1. Application of the proposed risk model to safe speed identification

In this paper, we proposed a novel safe speed identification method based on navigation risk assessment. The safe speed identification was based on the BN's network updating. When the state of a node is observed or confirmed, it can be regarded as observed evidence; thus, the network can be updated, as well as the probabilities of accident occurrence, consequence, and risk. Moreover, in real Arctic navigation, information about ice concentration from the observation of the crew is the primary source to know the ice condition of the ice field, while it is difficult to obtain data about ice thickness, or their accuracy is very rough. Thus, this model can be used to identify the safe speed under different ice concentrations.

Using the method mentioned above, three scenarios have been discussed in the current study, namely the light ice scenario, the medium ice scenario, and the severe ice scenario. They were chosen depending on the distribution of the states of the node "ice concentration". To make the results more visible, the risk index was attributed according to the level of risk, for which high, medium, and low values of composite risk corresponded to risk index values of 100, 10, and 1, respectively. In this Section, we used the case of the "Yong Sheng" to demonstrate the method of safe speed identification.

In the first scenario, the ice condition was initially set as a 100% probability of being "lower than 50%". After that, the state of the node "ship speed" was adjusted sequentially, and the developed BN could be updated after every adjustment. The risk distribution of the "composite risk" could be obtained, and the corresponding risk index could be calculated, as shown in Fig. 7.

It can be seen that when the ice condition is light, i.e., when ice concentration is below than 50%, the safe speed could be over 11 kn with the lowest risk level. Then, the state of the node "ice concentration" was adjusted to "50–70%", which represents the medium ice scenario. The result for this scenario is shown in Fig. 8.

In the medium ice scenario, the risk change trend is different than in the light ice scenario, as it first decreases and then increases, reaching the lowest risk value at speed "8–11 kn". Finally, the state of the node "ice concentration" was adjusted to "over than 70%", to obtain the severe ice scenario. The result is shown in Fig. 9.

In this scenario, a relatively lower ship speed range, from 5 kn to 8 kn, has the lowest risk level, while the range over 11 kn has the highest risk value. The safe speed under different ice conditions can be thus inferred according to the proposed model.

6.2. Ship safe speed in ice-covered waters

Generally, the Arctic navigation risk protection or decline can be classified into two categories, namely passive and initiative protection. Passive protection refers to the measures to enhance the structural strength; this is of considerable significance, although it is very expensive and inefficient. Furthermore, the evaluation of the ship structural performance during accidents, and the corresponding risk, are challenging issues due to large uncertainties in ship-ice impact analysis (Kubat et al., 2016). In parallel, initiative

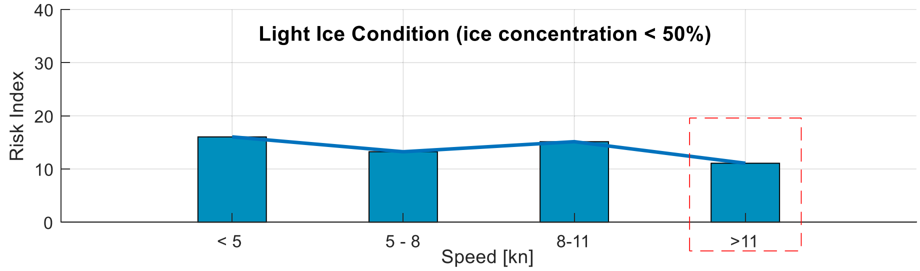

Fig. 7. Risk index change diagram (the red-dotted rectangle represents the safe speed with the lowest risk index under light ice conditions).

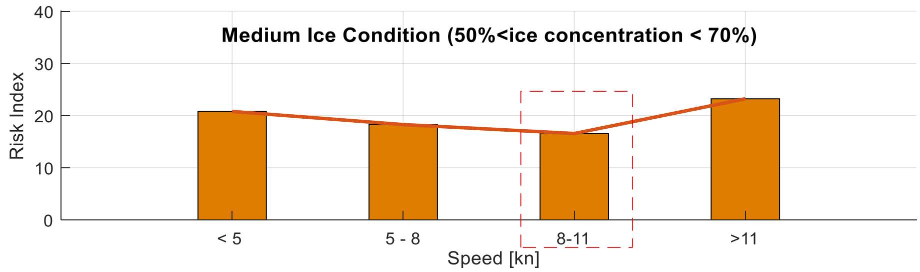

Fig. 8. Risk index change diagram (the red-dotted rectangle represents the safe speed with the lowest risk index under medium ice conditions).

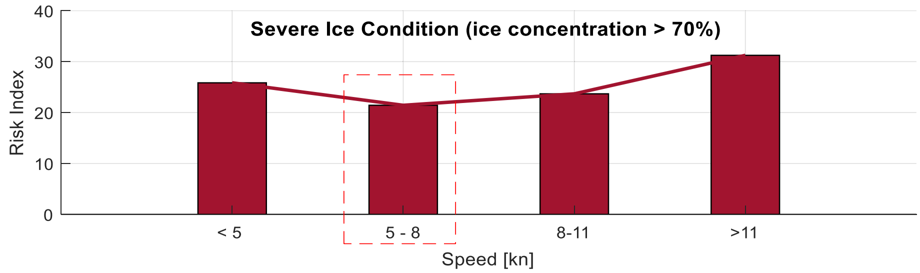

Fig. 9. Risk index change diagram (the red-dotted rectangle represents the safe speed with the lowest risk index under severe ice conditions).

protection focuses on aspects such as channel management and navigation improvement. Navigation with safe speed is a kind of navigation improvement that can be considered as an initiative protection measure; this was also the motivation for proposing the safe speed identification method presented in section 6.1. However, no clear criteria or guidelines are available for operators to identify the safe speed in ice-covered waters.

Ship speed in ice-covered waters is generally considered as the joint result of ice conditions and of the thruster. In their work, ENFOTEC et al. (1996) defined the safe speed for ships in ice-covered waters by analyzing the Canadian Arctic Ice Regime Shipping System (AIRSS). Safe speed was defined based on the encountered ice conditions and the ship's ice class according to the AIRSS. This regression-based approach can make use of historical voyage data and navigation experience to assess the relationship between safe speed and ice condition for ships with different ice classes by averaging other factors, e.g., ship type. This method was applied to estimate the safe speed for our case study ship under three ice conditions. A comparative analysis was also performed by using the method proposed, as shown in Table 10.

From the comparative analysis, it can be seen that the safe speeds identified by these two methods are substantially in agreement, although the method proposed by ENFOTEC et al. (1996) slightly underestimates safe speed in all ice conditions. The reason may be

Table 10
Comparative analysis of two safe speed identification methods.

Ice concentration	Safe speed	
	Method proposed in this paper	Method proposed by ENFOTEC et al. (1996)
Light (0–0.5)	11–13 kn	6.8–13.5 kn
Medium (0.5–0.7)	8–11 kn	5.2–9.5 kn
Severe (0.7–0.9)	5–8 kn	4.1–7.5 kn

that it did not consider the risk of getting stuck in the ice, for which the speed should not be too slow.

7. Conclusion

In this paper, an integrated risk assessment model for ice-going ships was developed based on BN methodology. To overcome the limitation of insufficient objective data, expert judgment and literature were considered in this model. Unlike other research focusing on a single risk scenario, the major innovation of our research lays in the fact that two different but connected accident scenarios, i.e., getting stuck in the ice and ship-ice collision, were considered into one risk assessment model. A case study was performed using the voyage data collected from Yong Sheng's Arctic sailing in 2013. The validation was conducted by performing a sensitivity analysis and through the BN validation framework. Based on the model sensitivity analysis, we found that for the case study ship, the risk of getting stuck in the ice is more sensitive to ice concentration and thickness, while ship-ice collision risk is more sensitive to ice concentration and ship speed. Moreover, the application of the proposed model, a method to identify the safe speed for Arctic navigation, was conducted from a multi-risk perspective. The results of this study can be used in the evaluation of safe Arctic transit conditions and route planning, and for shaping the Arctic policy, all of which aim at assisting Arctic navigation to enhance safety. However, several limitations or drawbacks still exist and deserve further investigation. For example, the severity of every possible consequence was evaluated using expert opinions, a method that is too subjective. It is advisable to improve the evaluation by integrating it with more objective data, such as ice tank experiment data and full-scale measurement data. Also, we neglected the effect of ice ridges, which should be considered in future work. Moreover, because of lack of objective data, the model can only provide a safe speed range. Thus, collecting more data may help to improve the accuracy of safe speed identification.

CRediT authorship contribution statement

Chi Zhang: Writing - original draft. **Di Zhang:** Conceptualization, Writing - review & editing. **Mingyang Zhang:** Methodology. **Xiao Lang:** Data curation. **Wengang Mao:** Conceptualization.

Declaration of Competing Interest

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

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