Ocean Engineering 203 (2020) 107205

Contents lists available at ScienceDirect

Ocean Engineering

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

Dynamic risk assessment of natural environment based on Dynamic Bayesian Network for key nodes of the arctic Northwest Passage

Heng Qian [a], Ren Zhang [a,b,*], Yao-jia Zhang [c]

[a] College of Meteorology and Oceanography, National University of Defense Technology, Nanjing, 211101, China

[b] Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science &Technology, Nanjing, 210044, China

[c] China Business School, University of Birmingham, UK

ARTICLE INFO

Keywords:
Arctic northwest passage
Key node
Dynamic Bayesian network
Dynamic evaluation

ABSTRACT

Recent global warming has made it possible to exploit and utilize resources in the Arctic Northwest Passage. However, the harsh natural environment in this sea area poses a major threat to safety during navigation. Although this passage is extensive, the natural environmental state of few key nodes affect the navigability of the entire passage. In this paper, we describe dynamic assessment of natural environmental risks of key nodes in the Arctic Northwest Passage using Dynamic Bayesian Network (DBN). Specifically, index selection and data processing, determination of key navigation nodes, calculation of evidence-based reasoning and verification of DBN-model are discussed. Results show that the DBN-model effectively handles uncertainty of information, and generates highly accurate inference results. In addition, it integrates historical information in the reasoning process, enables accumulation of information, reduces the influence of data errors on the final result, and makes the result closer to the real value. Overall, this model provides an important reference for judging the comprehensive risks of natural environment at key nodes.

1. Introduction

The Arctic Northwest Passage generally refers to a passage traversing the Beaufort Sea (in Northern Alaska), the Canadian Arctic Archipelago waters, Eastern Davis Strait and Baffin Bay, and finally the Pacific and Atlantic Oceans. Due to its unique geographical location, it can be predicted that this Passage will play a vital role in the shipping industry. In fact, according to Borgerson (2008), it has shortened the voyage from Seattle to Rotterdam by 2000 n miles, saving 25%. Due to such advantages, this passage has attracted the attention of many countries. In 2008, MV Camilla Desgagnés set off from Montreal, Canada, and became the first merchant ship to use the passage. In 2014, the “NUNAVIK” ice-breaking bulk carrier set out from Disepchen Bay and traveled alone through the entire Northwest Passage to reach Ying Kou Port in China. Traditionally, the Panama Canal has been the only trade route between China and North America. These successful attempts indicate a more economical passage for trade between China and North America (Stephens, 2016). Through the passage, trade voyages between China and North America have been shortened by 40%, emissions reduced by 1300 tons, resulting in considerable savings (Li, 2016). In September 2017, China’s “Snow Dragon” polar scientific research vessel crossed the Northwest Passage for the first time, directly promoting China’s commercial use of the Arctic Passage. Opening of this channel not only provides an additional navigation option, but also enables change of economic strategic status for countries along the route. The Northwest Passage has many advantages compared to the traditional passage. These include a short channel distance, low shipping costs, simple geopolitics, and low risk of pirate attacks (Zou and Huang, 2016). However, because it is located in a high latitude region, the channel also faces disadvantages, such as imperfect infrastructure, a fragile ecological environment as well as poor emergency response and rescue capabilities. Additionally, it is frozen for most of the year, and cannot, therefore, be efficiently utilized (Stephens, 2016). Research on global warming in recent years, shows that the Arctic region is warming twice as fast as the rest of the world. According to the current trends in climate change, the area around the Arctic sea will be completely ice-free as early as the summer of 2050 and all year round by 2100. This means that the navigation period of this passage will be greatly prolonged and its

* Corresponding author. Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science & Technology, Nanjing, 210044, China.

E-mail addresses: qian618_nudt@163.com (H. Qian), zrpaper@163.com (R. Zhang).

https://doi.org/10.1016/j.oceaneng.2020.107205
Received 21 August 2019; Received in revised form 2 March 2020; Accepted 2 March 2020
Available online 25 March 2020
0029-8018/

navigable conditions significantly improved, making it possible to exploit polar resources (Sou and Flato, 2009; Khon et al., 2010; Dan et al., 2015). The first requirement, for whether a passage can be opened and accepted by everyone, is safety during navigation. It has, therefore, become increasingly necessary to perform safety risk analysis of the Arctic Northwest Passage.

Currently, there are two kinds of risk assessments for Arctic shipping lanes. The first one analyzes risk-causing mechanisms of each influencing factor. Here, these factors are organically integrated to obtain an intuitive risk state assessment for selecting and adjusting a navigation route. The other builds a risk assessment model for traffic accidents in Arctic navigation channels. Specifically, maritime accidents are taken as the research object and used to estimate risks of accident scenarios and associated consultations. This information is further used to support ship operation decisions, thereby minimizing navigation and operation risks in Arctic waters.

The first type of risk assessment has generated the following developments. Pharand (2007) examined possible disputes over the right of transit passage, following the opening of the Northwest Passage, and predicted that a gradual opening of the passage would increase social and political risks. The Fuzzy Analytic Hierarchy Process (FAHP) approach and grey fuzzy comprehensive evaluation method were subsequently used to identify and quantify navigation risks of the Arctic channel based on expert experience (Li et al., 2012; Sahin and Kum, 2015). In addition, Fu et al. (2016) used the Bayesian Belief Networks (BBN) to develop a causal probabilistic model that predicts the probability of a ship getting stuck in ice of the Arctic waters. In this causal model, a set of input parameters such as hydro-meteorological conditions (air temperature, ice concentration, ice thickness, sea temperature, wave height and wind speed) along the analyzed route were considered.

The second type of risk assessment has also generated numerous developments to achieve better predictability. For instance, Kum and Sahin (2015) educed a Fault tree (FT) model, for estimating the probability of failure resulting from combinations of faults, to analyze navigation-related accidents and their causes in the Arctic from 1993 to 2011. It must be pointed out here that this model borrows Ferdous's theoretical framework and uses fuzzy approach with FT technique to reduce the ambiguity and imprecision arising out of subjectivity of the data (Ferdous et al., 2009). However, the FT model mainly analyzes the cause of the accident. In order to carry out a detailed investigation from the basic cause to the final result, a Bow-Tie (BT) diagram model has been applied, which is a combination of the fault and event tree. In this model, the event tree (ET) is a mature risk analysis technique used to assess the likelihood of an accident (Huang et al., 2001). But without addressing the incompleteness and inaccuracy in the available data and the inflexibility to absorb new knowledge (evidence), the credibility of BT and subsequent risk analysis remains a major issue. In order to solve the above problems, Ferdous et al. (2013) used fuzzy sets and evidence theory to characterize the uncertainty associated with expert knowledge, while merging the knowledge of multiple experts and updating existing knowledge with new evidence, effectively increasing the credibility of quantitative assessment. Models based on this framework have also been applied in Arctic shipping and accident. For example, Abbassi et al. (2017) used the BT relationship to represent causes of accidents, their consequences and the probability of occurrence during navigation in arctic waters. However, this model is incapable of handling accident scenarios where redundant, common cause or dependent failures occur (Khakzad et al., 2011). Furthermore, it does not use real-time information to update probabilities of failures in primary events and safety barriers (Khan et al., 2014). To overcome these limitations and dynamically assess transportation risks, the Bayesian Network (BN) was proposed for modeling accidents. Khan et al. (2014) proposed a causality based approach, using BN, to estimate the probability of maritime accidents and their related consequences. Similarly, Afenyo et al. (2017) used BN to analyze the collision scenarios between the ship and the Arctic iceberg. The use of Bayesian network offers analysts the opportunity to model interdependencies among the casual factors, which is not possible in conventional methods like the FT. In addition, Baksh et al. (2018) proposed a new risk model, in which BN is applied to the Northern Sea Route (NSR), to investigate the possibility of marine accidents including collision, foundering and grounding. This model considers different operational and environmental factors that affect shipping operations, with their base values (prior values) estimated using historical data and expert judgments. Experimental results obtained from this model identify ice effect as the dominant factor in accidents. Zhang (2014) concluded that BNs could combine objective data with subjective knowledge to handle these uncertainties. The discussion above show that BN is an effective approach for modeling maritime risks. However, some limitations in standard BN representation make it difficult to learn, construct, update, infer and reason complex models (Khan et al., 2018). To overcome these shortcomings, Object Oriented Bayesian Network (OOBN) is proposed for modeling and analyzing accidents. This model particularly predicts the probability of ship-ice collision considering navigational, operating and human factors (Khan et al., 2018). In order to deal with the threat of ship oil spill to the ecologically fragile Arctic waterway, Afenyo et al. (2019) also applied the OOBN model to study oil spill mitigative measures. This model overcomes the complexity, lack of data, and uncertainties in an oil spill and response modeling scenario for Arctic shipping accident occurrence.

So far, Arctic channel risk assessment modeling cannot adequately visualize waterway risks through the fusion of risk-causing factors. Analysis of accidents is developing towards quantification (BT-model), dynamics (BN-model) and modularization (OOBN-model).

Numerous factors affect the safety of ship navigation. These include technical faults, including ship navigational system states and operational system states; environmental conditions, such as ice and weather states; social factors, including local regulations, pirates and economic disputes; human error (Rothblum, 2000; Bowditch, 2002; Advisory, 2009; Canadian Coast Guard, 2012; Advisory, 2014; Sahin and Kum, 2015; Environment Canada, 2016; Khan et al., 2018). However, quantitative characterization cannot be currently directly performed due to a high degree of uncertainty in internal causes such as technical failures of ships and human-caused operational errors. This article, therefore, focuses on analysis and quantification of risks in the environmental conditions module. By consulting several literatures and analyzing the unique climate and geographical location of the Arctic region, we will discuss the characteristics of the natural environment of the Northwest Passage from two aspects: meteorological environment and hydrological environment.

There are many routes in the Northwest Passage. Generally speaking, only the natural environment of some key nodes influence the overall navigability of the passage (Fu, 2012). We evaluate natural environmental conditions in several key sea areas of the Northwest Passage.

Through reviewing the past researches, We integrate various risk factors to obtain intuitive risk assessment. The common theoretical evaluation methods currently in use include AHP, FAHP and BN. Due to the strong subjectivity of AHP and fuzzy evaluation, it is difficult to express, and deal with, uncertain information. In addition, these methods are unable to use the accident precursor information to revise the risk profile (Kalantarnia, 2009). In order to overcome this shortcoming, Kalantarnia (2009) introduced the concept of " dynamic risk assessment " and used Bayesian theory to update the likelihood of the event occurrence and also failure probability of the safety system. In case studies, the importance of learning and prediction tools in risk assessment is demonstrated by comparison with traditional methods. BN is built under the framework of Bayesian theory, so it also overcomes the deficiencies of AHP and FAHP in risk assessment to a certain extent. BN can calculate the probability of unknown parameters, as well as update that of known variables, using conditional probability (Kjaerulff, 1995), but it is limited in dealing with dynamic time series information. In fact, the general BN is static. For example, the joint probability distribution is usually a representation of a fixed point or an interval of time

(McNaught and Zagorecki, 2010). Furthermore, BN does not consider the correlation and mutual supplement of the information before and after time, so it cannot realize dynamic evaluation. Dynamic Bayesian Network (DBN) describes the evolution of joint probability distribution over time, and thus extends the BN. Discrete time modeling, proposed by Dean and Kanazawa (1989), represents progression of time in the DBN. In DBN, arcs links nodes from previous time slice to that of the next time slice to represent temporal dependencies among them. Montani et al. (2005) included temporal aspects to perform reliability analysis to demonstrate capabilities of DBN in a dependability analysis. Therefore, application of DBN would improve flexibility during risk analysis.

As a new intelligent knowledge expression and reasoning tool, DBN has strong advantages when dealing with uncertain expression of time series information and reasoning problems related to complex structures. Its application in dynamic evaluation and prediction is expected to set the trend for future development. Currently, few studies have investigated the used of DBN for intelligent modeling. The focus has been on assessing safety of production and transportation processes. However, application of this tool for environmental risk assessment in the Arctic sea has not been tested. The available documents only allow preliminary assessment modeling and perform analysis based on DBN (Khakzad et al., 2012; Pauplin and Jiang, 2012; Barua et al., 2016; Li et al., 2018; Zeng and Zio, 2018). However, in these studies, manual determination of network structure and parameters was completely based on expert knowledge, and not objective data analysis, and therefore, lacks the process of automatically learning node parameters from actual data, which is highly subjective.

Based on the above correlation analysis, this paper relies on quantification, dynamics and modularization concepts. We begin with the natural environment module, target key nodes on the passage and relies on the theory of DBN. On the basis of analysis of risk factors of marine environment in key sea areas of the Northwest Passage, establishment of network structure, learning of node parameters and reasoning calculation, a DBN-model for assessing the natural environment in the Arctic is established. This is based on expert knowledge and objective data, combines prior information and updated evidence information. It also fully considers the time effect of information accumulation to achieve quantitative, dynamic and modular risk assessment.

The rest of the paper is structured as follows: Section 1 introduces the risk-causing mechanism, data sources, normalization scheme and interannual distribution characteristics of the risk-causing factors selected in this paper. A number of key nodes on the Northwest Passage are identified in Section 2, while Section 3 generates discretized sample data sets. A case study is presented in Section 4 to describe the application of the method. The accuracy and validity of the DBN risk assessment model are verified in Section 5.

2. Index selection and data source

We utilize the unique climate and geographical location of the Northwest Passage to identify causes of risks in natural environment (meteorological and hydrological environment) and define its risk-bearing body and related consequences. The effect of various risk-causing factors is shown in Table 1.

2.1. A risk indicator system for natural environment safety

According to the analysis described above, ships and personnel sailing in the Northwest Passage were used as risk carriers to identify the main risk factors affecting the meteorological and hydrological environment. The selected factors are shown in Table 2.

2.2. Discriminating layer meaning, risk mechanism, data source and quantitative method

The indicators are defined and quantified, to ensure a strong intuitive reflection of their attributes and characteristics. Based on objective facts and predecessors (Bai et al., 2009; Lu, 2012), this section redefines and quantifies the five indicators in the previous section.

2.2.1. Gale risk index (d1)

Definition: Gale risk index refers to the degree of threat from gale weather to vessels in the target area, and is mainly reflected by the wind speed.

Risk mechanism: In case of gale, it is easy encounter accidents, such as yaw, anchoring and stranding of the ship. When sailing in the polar regions, the wind also blows ice floes, posing a potential threat to the ship.

Data Sources and Description: Wind speed is extracted from the ERA high-precision monthly average reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF), which records worldwide meridional and zonal wind speeds. To obtain the latest natural environmental risk characteristics of the Northwest Passage, monthly average data from 2005 to 2016 is selected as the time series.

Quantification formula:

$$\mathrm{d1} = \begin{cases} \dfrac{w^2}{w_{\min}^2} & w \le 10.8 \\ 1 & w > 10.8 \end{cases} \tag{1}$$

According to energy science, the intensity of strong winds depends on wind speed. In formula 1, w denotes the original value of wind speed in the evaluation unit, while $w_{\min}$ is the lowest standard value of the strong wind, with a value of 10.8 m/s (Yang et al., 2013).

2.2.2. Visibility risk index (d2)

Definition: Visibility risk index refers to the extent to which visibility in a target area threatens the safety of vessel in the sea. The larger the indicator value, the greater the risk.

Table 2
The natural environmental safety risk indicator system.

Target layer (A)	Discriminant layer (D)
Arctic Northwest Passage meteorological environmental safety risk A1	Gale risk index d1 Visibility risk index d2
Arctic Northwest Passage hydrological environmental safety risk A2	Sea ice thickness hazard index d3 Sea ice intensity hazard index d4 Sea temperature risk index d5

Table 1
Identification of natural environmental risks in the Northwest Passage.

	Pregnancy environment	Risk factors	Insurance body	Risk consequences
Comprehensive risk of natural environment in the Northwest Passage	Meteorological environment	gale, sea fog, low temperature	ship, personnel	channel pollution or blockade, port facilities damaged, ship caps, rocks, damage, infrastructure damage, casualties
	Hydrological environment	ocean waves, icebergs, rapids	infrastructure, ships, personnel	

Risk mechanism: In meteorology, visibility refers to the maximum horizontal distance that can be seen by normal eyes. When sailing in the Arctic, factors that affect visibility mainly include sea fog, snow blowing, hail, etc. Among these, fog is the most important factor. During low visibility conditions, it is difficult to identify obstacles, which may lead to collision between ships and ice. July and August is the best time for ships to navigate owing to the melting of sea ice. However, frequent advection fog compromises the safety of ships.

Data sources and brief introduction: The monthly average visibility data from 2005 to 2016 are obtained based on BP neural network regression inversion algorithm (Shan et al., 2019). The scheme uses the relevant factors such as aerosol, relative humidity, precipitation, etc. that affect visibility to carry out visibility inversion by constructing BP network and corrects the deviation by combining the ocean visibility data from the stations (released by the National Climate Data Centre of the United States).

Quantification formula:

$$d2 = 1 - \frac{V - V_{\min}}{V_{\max} - V_{\min}} \quad (2)$$

In the formula, V is the original visibility value of the evaluation unit, while $V_{\min}$ and $V_{\max}$ are minimum and maximum visibility values in the study sample area, respectively.

2.2.3. Sea ice thickness risk index (d3)

Definition: Sea ice thickness hazard index refers to the threat level posed by thickness of sea ice to the shipping vessel in a target area.

Risk mechanism: Larger sea ice thickness indicates thicker ice. Based on this, it will bring great challenges to the ship's ability to break ice, increase the possibility of the ship being stuck, which compromises rescue efforts in the event of ship accident.

Data sources and brief introduction: sea ice thickness data are generated from the monthly averages in the output of the pan-arctic ice ocean modeling and assistance system (PIOMAS) sea ice model released by the University of Washington in the U. S.

Quantification formula:

$$d3 = \frac{K - K_{\min}}{K_{\max} - K_{\min}} \quad (3)$$

In the formula, k is the original value of sea ice thickness of the evaluation unit, while $K_{\min}$ and $K_{\max}$ are the minimum and maximum values of the sea ice thickness in the study sample area, respectively.

2.2.4. Sea ice density risk index (d4)

Definition: Sea ice density risk index refers to the degree of threat of sea ice to shipping vessels in a target area. The higher the concentration of sea ice, the greater the risk.

Risk mechanism: The higher the concentration of sea ice, the more ice there is on the sea surface. This risk index (d4) tests the continuous ability of ships to break ice, and further increases the probability of formation of floating ice (iceberg), which endangers the safety of ships.

Data source and brief introduction: Sea ice density is extracted from the ERA high-precision monthly average reanalysis dataset. Monthly average data from 2005 to 2016 is selected as the time series.

Quantification formula:

$$d4 = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \quad (4)$$

In the formula, I denotes the original value of sea ice density of the evaluation unit, while $I_{\min}$ and $I_{\max}$ are minimum and maximum values of sea ice density in the study sample area, respectively.

2.2.5. Sea temperature risk index (d5)

Definition: Low temperature risk index refers to the degree of threat to shipping vessels caused by low sea surface temperatures in a target area.

Risk mechanism: When sailing in the Arctic region, low temperature influences ships in the following aspects: firstly, low temperature causes the sea surface to freeze and form an ice layer which impairs ship navigation. Secondly, when the ship is sailing, waves, rain and snow cause ice accretion (when the temperature is relatively low), thereby indirectly affecting its navigation. Lastly, low temperature decreases the living conditions of the crew, inconveniencing their normal life and work. This inevitably affects operation of the ship (Xie, 2014).

Data sources and brief introduction: sea surface temperature is extracted from the ERA high-precision monthly average reanalysis dataset. Monthly average data from 2005 to 2016 is selected as the time series.

Quantification formula:

$$d5 = \begin{cases} 0 T > 0^{\circ}C \\ \left|\frac{T - T_{\min}}{0 - T_{\min}}\right| T \leq 0^{\circ}C \end{cases} \quad (5)$$

In the formula, T denotes the original value of Sea Surface Temperature (SST), while $T_{\min}$ is minimum value of SST in the study sample area, respectively.

2.3. Spatial distribution characteristics of climatic state of each index in an ideal navigation period

In this paper, Northwest Passage and its surrounding waters are taken as the target area, spanning from 60 °W to 135° W, 66 °N-77 °N coordinates. According to previous research, July–September is the ideal navigation period in this passage (Howell et al., 2009). Therefore, we calculate the multi-year (2005–2016) climatic average value of each index from July to September. Based on this, spatial distribution of the climate natural indicators, in the time period when the passage is most likely to be opened, are analyzed (see Fig. 1).

Based on sea ice density, ice in the Northwest Passage covers the low east and high west regions. The risk of Busia Bay and the McClintock Strait is higher, lower in Baffin Bay. In terms of sea ice thickness, it is evident that the waterway is generally in a low-risk state, while the channel between Victoria Island and Prince of Wales in high risk state. Based on temperature, the findings show that the risk in some sea areas (such as the McClintock Strait) is high. Moreover, the wind speed poses medium to low risk in the Northwest Passage, but high risk in the McClintock Strait and Busia Bay. In terms of visibility, the Northwest Passage is generally at medium to low risk, but the relative risk increases at high latitude regions.

3. Determination of key nodes in the Northwest Passage

As can be seen from the above, the status of influence factors varies from place to place in the Northwest Passage. In actual navigation, navigation routes are usually determined according to the specific application conditions. If the risk assessment is carried out for the entire Northwest Passage, the efficiency decreases as well as the significance. Several key nodes in these channels cannot be avoided in actual navigation. Its natural environment is of great significance for navigation. If the key sea areas are not navigable, the entire route basically cannot be traversed. In this section, we will focus on the selection of key nodes in the general route of the Northwest Passage.

3.1. Determination of key sea areas in the Northwest Passage

Although the global views on the general route of the Northwest Passage are similar, this is not the case for the specific route of the Northwest Passage. Analysis of different aspects of this Passage has identified 7 main routes, namely, North Northwest Passage Road (NNPR), Prince of Wales Strait (PWS), Peel Strait (PS), Peel Strait (PS) adjustment route, Prince Regent Inlet (PRI), Prince Regent Inlet (PRI)

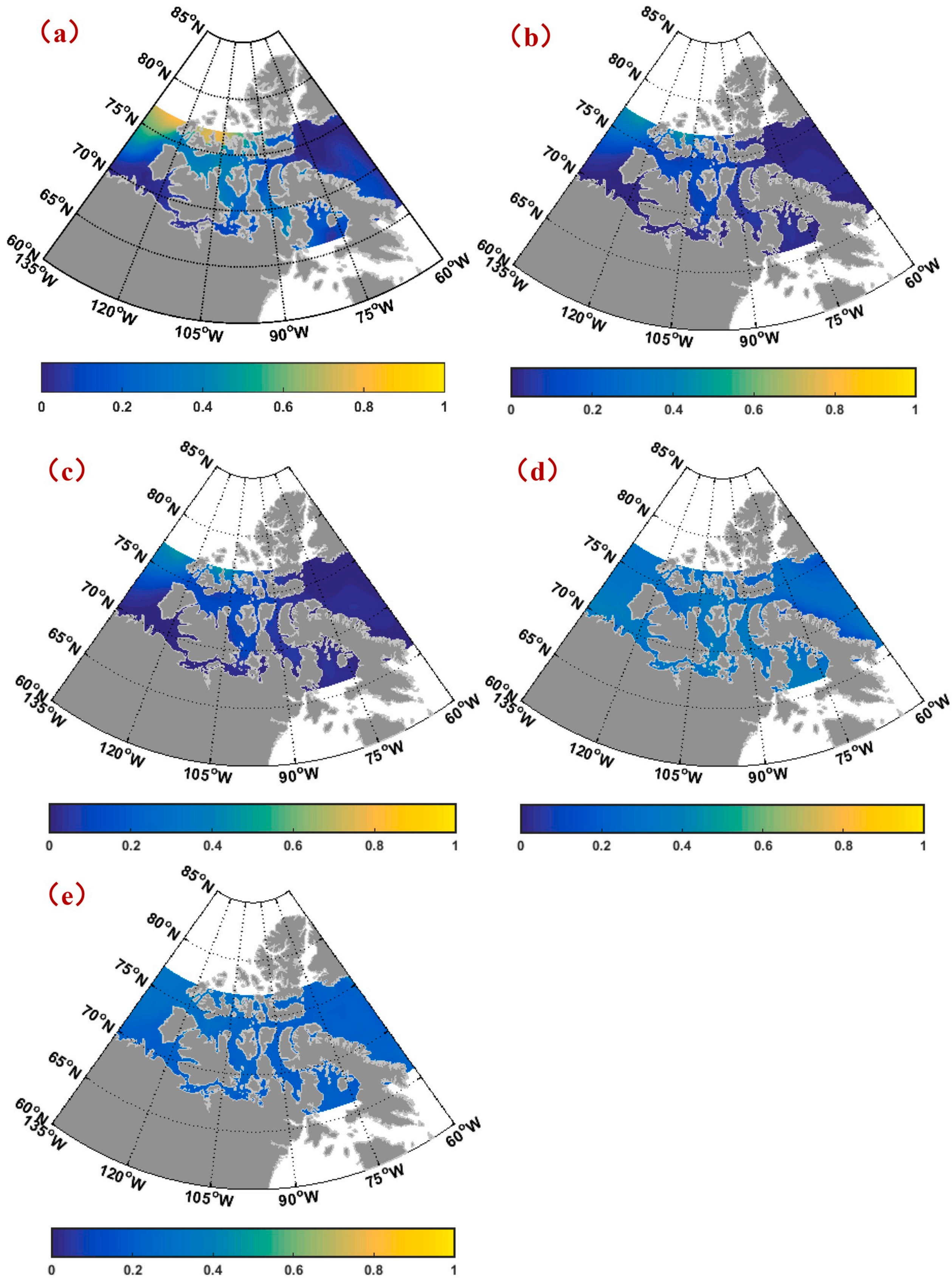

Fig. 1. The average annual status of natural navigation index in the Northwest Passage ((a) sea ice concentration; (b) sea ice thickness; (c) sea surface temperature; (d) sea surface wind speed; (e) visibility).

adjustment route 1 and Prince Regent Inlet (PRI) adjustment route 2 (Pharand, 2007).

From historical studies (Fu, 2012; Jie et al., 2010), the opening degree of the Northwest Passage is largest in August and September in a given year, while the number of navigable sea areas in October and November have declined sharply in recent years, making it almost impassable. On average, all waters except Barrow Strait, Lancaster Sound and the Northern waters of Victoria Strait open in August, These waters partially open in mid-September. Therefore, we identify three key sea areas that affect or determine whether the Northwest Passage of the Arctic is navigable, i.e., the Ba-Lan key area, the Ba-Mai-Mei key area, and the northern sea area of the Victoria Strait.

Among them, Ba-Lan is located at the eastern exit of the Northwest Passage, which is the preferred exit for all routes except route 7. Since the condition of routes along Route 7 are not favorable, we infer that Ba-Lan key area is the only area that affects the navigability of the entire Northwest Passage (Fu, 2012). A key advantage of this area is that it receives the West Greenland Warm Current (Jie et al., 2010). Although it is difficult to navigate in August, the sea area is navigable in September. When sea ice extent is at minimum, there is almost no ice in the Ba-Lan key area. Thus, the Ba-Lan key area (73.5°N-74.5°N, 90°W-75°W) is finally chosen as the research focus. The changes of natural environment risks in this sea area are determined using real-time data.

3.2. Determination of key nodes

Based on recommendations in the book called Arctic Navigation Guide (Northwest Passage) 2015, we identified several points (Maritime Administration of the People's Republic of China, 2016) by considering several factors such as hydrometeorology, sea ice, rescue and logistics services, obstruction of navigation and prohibition of navigation as shown in Table 3 and Fig. 2. Thus, we explore the selected key nodes in key sea areas of the Northwest Passage. We use No. 1 node in the key sea area of Ba-Lan as an example to study the dynamic changes in the natural environment risks in these sea areas using real-time data.

4. Generation of target node data

Target node data, i.e. the comprehensive risk value of natural environment, cannot be directly obtained through observation. Instead, it is obtained through calculation. Considering the limited operational experience and lack of historical accident information of the Arctic region, the value or probability distribution of the target node was previously generated randomly with Markov Chain Monte Carlo framework (Abbassi et al., 2017) or assigned based on experience (Khan et al., 2014). Herein, the risk factors are linearly fused to reduce the error. This section attempts to generate a complete sample set containing target node data in three steps.

4.1. Discretization of index data

For computational reasons, the BN is generally restricted to variables with discrete states (Straub, 2005), but the data of the selected indexes are continuous. Thus, it is necessary to discretize the continuous indexes and determine the grade of each index before learning the structure of BN, that is, to determine the status of network nodes. Given natural index data in this paper has already normalized, the traditional discrete method, interval equal interval partition method, is adopted in this paper. The specific partition methods are shown in Table 4. The continuous indexes are divided into discrete grades to generate discrete data sets.

4.2. Subjective and objective combination determination of the weight value

Considering that changes in index elements varies with time, and entropy weight method determines the weight based on the variation degree of index values, which uses the difference between the amount of information of each indicator data to determine the weight, thereby reducing the interference of human subjective judgments on the weight (Liu et al., 2011). Therefore, we employ the entropy weight method to determine the weight in this paper. However, the pure objective weight determination methods are also limited in some ways. If the subjective and objective methods are combined, this will avoid excessive reliance on expert knowledge and experience, and minimize the mismatch between the data information and the actual cognitive law. Therefore, we adopt a subjective method with wide application scope and good effect: G1 (Huang et al., 2008; Jing et al., 2013). The final weight value is obtained from the weighted sum of the weights determined by the two methods, with the subjective and objective methods yielding 0.4 and 0.6, respectively. The target node data can be obtained by weighting and summing the data of each observation node. The final combined weight values determined by subjective and objective methods are shown in Table 5.

The calculation results show that the weights of the No. 1 point in the key area of Ba-Lan are sea ice thickness (d3), sea surface temperature (d5), wind intensity (d1), sea ice concentration index (d4), and low visibility (d2). It can be seen that sea ice, especially its thickness, is still the most important factor hindering further opening of the channel. The thickness of sea ice is difficult to measure with ordinary equipment, resulting in insufficient quality data. When calculating the weight of low visibility index, the results obtained by entropy weight method and the G1-method are significantly different. The entropy weight method is based on the difference of the amount of information in the data itself. Due to the scarcity of data and the characteristics of the monthly average data in the Northwest Passage, the results of the entropy weight method have a certain deviation. Historical research showed that the importance of this indicator was undeniable (Khan et al., 2018). Therefore, the existence of the G1 method weakens the problem of the mismatch between the results of the entropy method and the objective situation. The final result of the weights is consistent with the actual situation of the natural environment elements.

4.3. Target node data generated by index fusion

Index fusion is a component of the risk assessment model. In this paper, the normalized index data and corresponding index weights are fused by weighted synthesis method. The fusion formula is as follows.

$$\text{Risk} = \sum_{i=1}^{n} w_i \cdot d_i \tag{6}$$

In this formula, Risk represents comprehensive risk value, w_i represents index weight, d_i represents index value, and n represents index number. Thus, a complete sample set is obtained. The sample set is arranged chronologically from January 2005 to June 2016. Based on the discretization scheme of sub-node data, the risk data set (continuous set) is first normalized with range method, and then discretized according to

Table 3
Location of key nodes.

Key sea area		NO.1	NO.2	NO.3	NO.4	NO.5
Ba-Lan key sea area	Geographical location	(74°20′N,97°w)	(74°05′N,91°W)	(74°10′N,89°W)	(74°10′N,80°W)	(74°N,76°W)
	Water depth/m	154	58	311	794	851

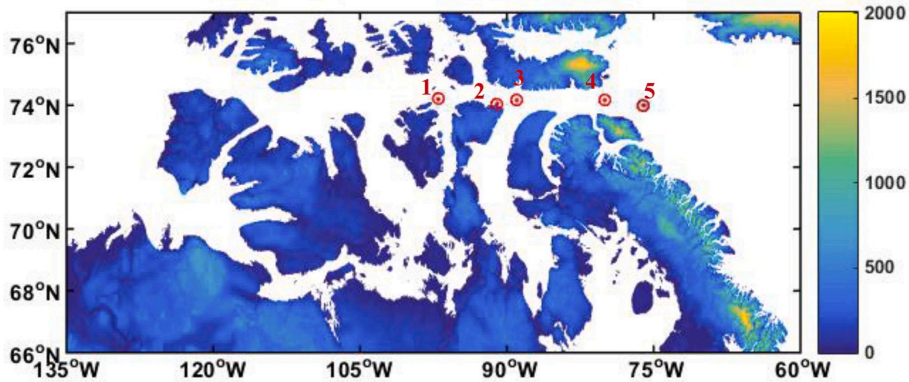

Fig. 2. Geographical locations of important node (key nodes in the Ba-Lan key area are shown as red dot circles). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 4
Index dispersion and grade division.

Risk status	Scope of data	Discretization value
Lower risk	[0,0.2)	1
Low risk	[0.2,0.4)	2
Medium risk	[0.4,0.6)	3
High risk	[0.6,0.8)	4
Higher risk	[0.8,1]	5

Table 5
Calculated index weights (Take NO.1 node in Ba-Lan key area as an example).

Indicator	Weight calculated by G1	Weight calculated by entropy weight method	Combination weight
Gale risk index d1	0.24517	0.11842	0.16912
Visibility risk index d2	0.10234	0.05630	0.07472
Sea ice thickness hazard index d3	0.50415	0.40415	0.44415
Sea ice intensity hazard index d4	0.04587	0.13539	0.09958
Sea temperature risk index d5	0.10239	0.28573	0.21239

the equal interval partition method in Table 4, obtaining the discrete set. The final Training sample set is shown in Table 6.

5. Assessment model for natural environmental risks in key nodes

In this section, DBN, an expanded BN model, is used for assessment modeling. The dynamic assessment and prediction analysis are carried out on the comprehensive risks of natural environment. For illustration purposes, this case study only focuses on No.1 node. The risk analysis process presented below can be replicated in other key nodes. Monthly average data for 138 months from 2005 to 2015 are used as the training samples, whereas monthly average data from July to December 2016 are the test samples, and the interval between adjacent time slices of the network is taken as 1 month.

5.1. *Risk assessment modeling based on Dynamic Bayesian Network*

The state of the natural environment is affected by several factors which are dynamic. To perform effective assessment of the natural environment and identify early warning signs, comprehensive, systematic and dynamic integration of uncertain information of diverse forms and sources is required. The DBN used in this study not only inherits the advantages of static BN, but also has higher dynamic data processing capability (Yu and Ding, 2014). DBN combines the historical information and the latest evidence in the reasoning process of the final result, to perform time accumulation and information update, and effectively reduces uncertainty in the process of information fusion and reasoning at different levels (Yi et al., 2012). Therefore, DBN-model is suitable for dynamic assessment of natural environment risk at key nodes. Nevertheless, even if we only carry out the risk assessment of the environmental condition module, the challenges of missing data and fuzziness still exists. Fortunately, Zhang (2014) postulated that combination of subjective and objective approaches may effectively reduce the uncertainty level. Thus, we adopt this method to build DBN. Fig. 3 displays the technical structure of DBN.

In this paper, expert knowledge is used for structural learning while objective data with EM intelligent algorithm is used for parameter learning.

5.1.1. *Introduction to the principle of Dynamic Bayesian Network*

DBN integrates causal relationships between different time slices and within the same time slice. It then performs dynamic analysis and prediction through quantitative reasoning (Wei et al., 2010). According to BN theory, DBN is a directed acyclic graph that describes the probability relationship between time series variables. This model comprises nodes, directed arcs and conditional probability distribution tables. It can be represented by a binary group $< N_0, N_{\rightarrow} >$(Feng et al., 2012):

N_0 represents the initial network, namely BN of the initial time slice, which defines the prior probability distribution of network nodes within

Table 6
Training sample set (Take No.1 node in Ba-Lan key area as an example, where 1 refers to January of 2005 and 136 refers to June of 2016).

Month		1	2	3	4	5	6	7	8	…	…	136	137	138
Node	Risk	3	2	3	3	3	2	2	1	…	…	3	3	2
	d1	3	1	2	2	2	1	2	2	…	…	2	2	3
	d2	2	2	2	2	2	2	2	2	…	…	3	2	1
	d3	2	2	3	3	3	3	2	1	…	…	2	2	2
	d4	5	5	5	5	5	5	4	3	…	…	5	5	4
	d5	3	3	3	4	5	1	1	1	…	…	3	5	1

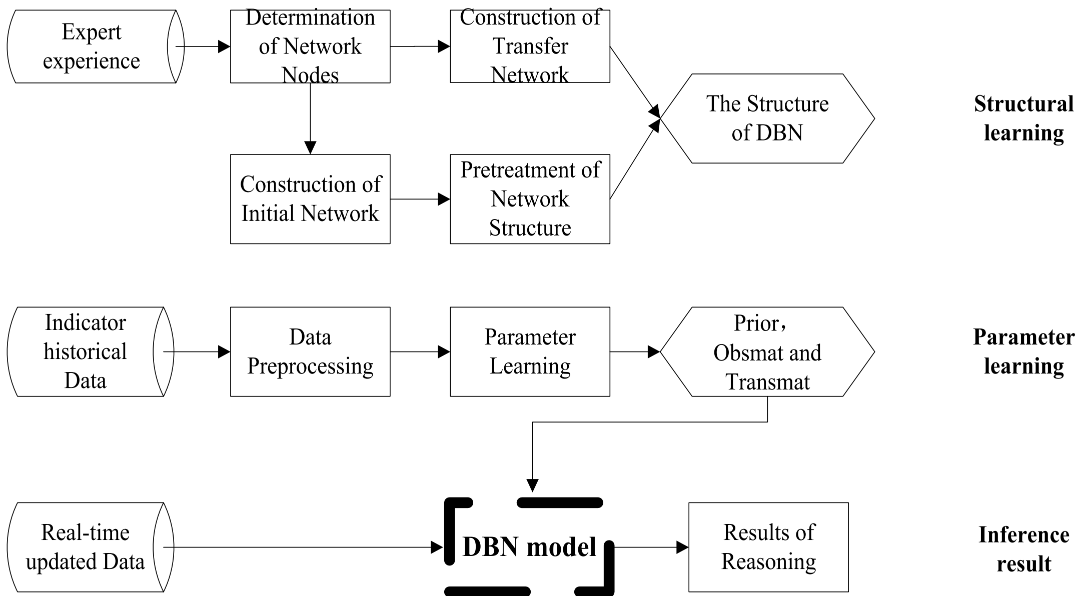

Fig. 3. DBN-model building process.

the same time slice.

$N_{\rightarrow}$ represents a transition network, which consists of BN of more than two time slices, and defines the transition probability distribution between nodes of different time slices.

The initial network of DBN represents the initial state of the network, the transition network reflects the correlation between adjacent time slices, and the magnitude of conditional probability between nodes reflects the strength of causality. DBN describes the causal relationship between variables, and also the evolution process of variables in time series, thus realizing the modeling and analysis of dynamic systems (Wei et al., 2010; Li and Liu, 2018).

Assuming variable set:$X = [X_1, X_2, \cdots, X_n]$, considering a finite period of time $[0, 1, \cdots, T]$, the joint probability distribution of $X^0, \dots, X^T$is:

$$P(X^0, \dots, X^T) = P(X^0) \cdot \prod_{t=1}^{T} \prod_{i=1}^{N} P[X_i^t | \pi(X_i^t)] \tag{7}$$

Where: X_i^trepresents node$i$at time t, $\pi(X_i^t)$represents parent node of X_i^t, probability reasoning of different time slices and different node states can be obtained through formula 7.

The DBN learning is an extension of BN learning in time sequence, which comprises structure learning and parameter learning (Wei et al., 2010). The difference is that the initial network N_0 and the transition network $N_{\rightarrow}$ should be constructed simultaneously in the structure learning of DBN. The initial state probability $P(X^0)$、observation condition probability $P[X_i^t|\pi(X_i^t)]$ and transition condition probability $P(X^t|X^{t-1})$ should be determined simultaneously in parameter learning. Currently, two commonly used DBN learning technologies are: manual establishment based on expert knowledge and automatic learning based on sample data with intelligent algorithms (Cussens, 2012).

5.1.2. Dynamic Bayesian Network structure learning

Because of the significant causal relationship between variables in the natural environment network modeling of key nodes, the expert construction method is adopted to improve the learning efficiency. Consequently, the network structure arcs of nodes in the same time slice and different time slices are determined based on the node variables selected above. Finally, the DBN structure is obtained from the network nodes and the dependency relationship, i.e. the initial network and the transfer network are determined, as shown in Fig. 4, where 1 is the natural environment comprehensive risk value at time t, 2–6 is the risk value of each indicator (d1-d5) at time t, 7 is the natural environment comprehensive risk value at time t+1, and 8–12 is the risk value of each indicator at time t+1.

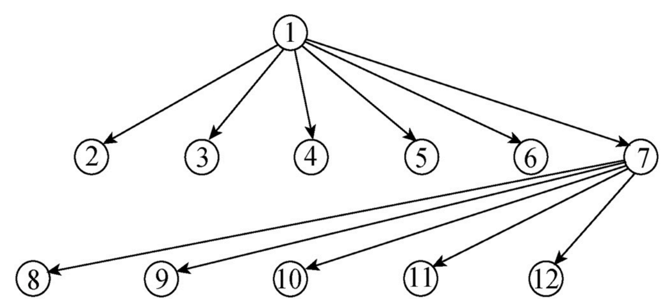

Fig. 4. DBN transfer network structure.

5.1.3. Dynamic Bayesian Network parameter learning

The DBN structure is built in the previous section. The next step involves learning the parameters constituting determination of the conditional probability distribution. The EM algorithm is used in parameter learning. It is divided into two steps (Lauritzen, 1995):

E step: Infers the distribution$\{P(\mathrm{R}|D, \theta^t)\}$ of the hidden variable R with the current parameter θ^t and observed variables D, and calculates the expectation of log likelihood $\{LL(\theta^t|R, D)\}$ for R :

$$\mathrm{Q}(\theta|\theta^t) = E_{\theta|\theta^t}[LL(\theta|D, R)] \tag{8}$$

M step: Finds the parameter to maximize the expectation likelihood:

$$\theta^{t+1} = argmax[\mathrm{Q}(\theta|\theta^t)] \tag{9}$$

Each network node is assigned a random probability distribution, including prior probability, observation probability, and transition probability when learning parameters. Subsequently, based on the inference mechanism and the input training data set, the EM algorithm is used to iteratively revise the node probability distribution and obtain the probability distribution most consistent with the objective training data (maximum likelihood estimation of each parameter). Taking the transition probability as an example, the final results are shown in Table 7.

Table 7
Transfer probability distribution of node R (Take NO.1 node as an example).

$P[R(T+1)\|R(T)]$	Lower risk (T)	Low risk(T)	Medium risk(T)	High risk(T)	Higher risk(T)
Lower risk(T+1)	0.2857	0.71429	1.00E-05	1.00E-05	1.00E-05
Low risk(T+1)	0.1666	0.4074	0.4259	1.00E-05	1.00E-05
Medium risk(T+1)	0.0149	0.3283	0.6268	0.0298	1.00E-05
High risk(T+1)	1.00E-05	0.5	0.5	1.00E-05	1.00E-05
Higher risk(T+1)	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05

5.2. Experimental evaluation of Dynamic Bayesian Network model

Network reasoning constitutes updating the state of network nodes based on the current or future information changes to realize the update and transmission of information using the causal relationship between nodes, and deduce the state distribution of target nodes. Specifically, first, the DBN is used in constructing a joint tree inference mechanism. Subsequently, evidence data is input to infer the probability distribution of the target nodes. In this paper, risk factors data are discretized and subsequently input as network evidence. This involves inputting the discrete values of observation node variables$\{d1, d2, d3, d4, d5\}$. The output value constitutes the probability distribution of the natural environmental state of the Arctic channel at different times as predicted by the inference. The natural environmental status of the NO.1 node is evaluated under Matlab 2014a environment using the DBN-model built in the previous section. The corresponding library functions required for this experiment are obtained from the BNT toolbox (FullBNT-V1.0.4.) written by K.P.Murphy (2018).

In this section, we input the test sample of the risk factors data from July to December 2016. The changes of each variable at this stage are shown in Fig. 5.

The DBN model is used for inference to obtain the probability distribution of the natural environment state at this stage. Finally, we choose the state corresponding to the maximum probability as the final evaluation result (shown in bold). The probability distribution of the natural environment state of NO.1 node at this stage is shown in Table 8.

The evaluation results indicate that the comprehensive risk of the natural environment of No.1 node increased monthly from July to December. The July to August risk was the smallest constituting the best airworthiness period.

Fig. 5 shows that the state of all risk factors is optimal from July to August, so the probability of feedback to the result corresponding to the "lower risk" level is highest in these five months. Thus, DBN-model can effectively capture the changes of the state of minor nodes, which is further reflected in the reasoning results. However, the risk level in the months of November to December is relatively high and the natural environmental factors are unfavorable for navigation safety. Based on the monthly changes of the sea ice condition (Baksh et al., 2018 pointed out that sea ice was the main natural cause of Arctic shipping accidents) at the NO.1 node, July to August is suitable, but this state worsens after August. Maximum levels of the speed of wind, the thickness of sea ice, and the sea ice density are observed from November to December. These evaluation results are consistent with the actual situation.

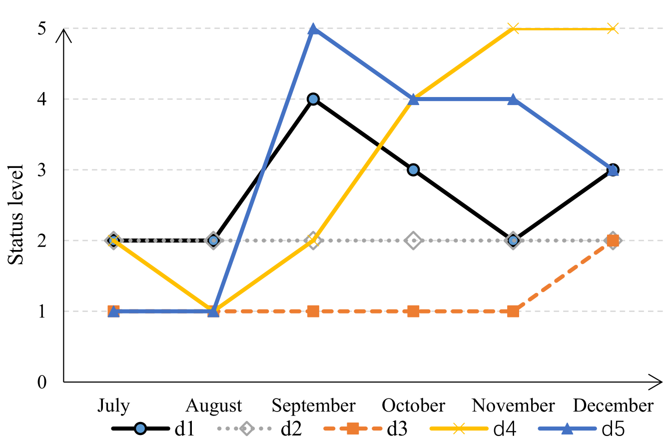

Fig. 5. The changes of each variable from July to December 2016.

6. Verification of accuracy and validity of the risk assessment model for Dynamic Bayesian Network

The above experiments confirm the applicability of the DBN-model in the navigation channels' natural environment risk assessment. Next, we compared the DBN-model to the FAHP Based on Triangular Fuzzy Stochastic Simulation (FAHP-TFSS) model and BN-model. Simultaneously, we performed the DBN-model updating reasoning experiment to verify the superiority of the technology on index data updating.

6.1. Comparative analysis of FAHP-TFSS comprehensive evaluation technology

FAHP-TFSS comprehensive risk evaluation model is based on the use of random simulation method to simulate triangular fuzzy numbers, simplifies triangular fuzzy numbers and inter-function operations into common real number operations, reflects the risk situation of the system under the comprehensive influence of various uncertain factors, and provides evaluation results in the form of confidence intervals (Jin et al., 2009). Compared with conventional methods (FAHP), FAHP-TFSS is more reliable in the form of confidence interval. At present, the FAHP-TFSS technology has been applied in the comprehensive risk assessment of various complex systems (such as water environment risk and basin flood risk, Wang and Chen, 2010; Jin et al., 2011, 2012), and is a good model to deal with the comprehensive assessment under various uncertain factors (incomplete, fuzzy and random data, etc).

The FAHP-TFSS model is used to evaluate the comprehensive risk in natural environment of the NO.1 node. The following risk value confidence intervals (confidence level 95%) are obtained from July to December 2016: [0.1222, 0.1996], [0.0958, 0.1726], [0.2805, 0.3649], [0.2975, 0.3803], [0.3100, 0.3918] and [0.3781, 0.4597]. The left end value of the confidence interval is denoted as FAHP-TFSS-LOW and the right end value as FAHP-TFSS-HIGH. Comparison results of these two evaluation models are shown in Fig. 6.

The FAHP-TFSS model uses triangular fuzzy numbers for stochastic simulation, but essentially combines various risk factors with expert experience. From the inference results obtained by the FAHP-TFSS model, it can be seen that the state of the natural environment improves (the value decreases) from July to August, and after August the state gradually worsens (the value increases). The DBN evaluation results in this paper also reveal this trend of change. Of note, the results of DBN-model are congruent with those of expert's empirical judgment, which illustrates the rationality of the evaluation results. Moreover, similar to FAHP-TFSS, DBN can objectively achieve the fusion of multisource information and dynamic reasoning, which increases the objectivity and accuracy of the results. Combining the time trends of hydrological and meteorological elements from July to December, the FAHP-TFSS reasoning results change too drastically from August to September, and too gentle from October to November. This is because FAHP-TFSS does not consider the effect of time on information.

Table 8
The probability distribution of the natural environment state of NO.1 node.

		time slice					
Comprehensive risk of natural environment in node NO.1	Risk level	July	August	September	October	November	December
	Lower risk	**0.9604**	**0.9720**	1.80E-08	1.46E-13	2.47E-10	3.26E-20
	Low risk	0.0384	0.0279	**0.9999**	**0.9250**	0.4628	0.1070
	Medium risk	0.0011	2.93E-09	3.91E-07	0.0749	**0.5371**	**0.8929**
	High risk	1.64E-21	2.90E-23	3.96E-17	1.48E-17	1.90E-16	5.33E-11
	Higher risk	2.91E-29	1.09E-34	7.92E-32	2.95E-32	1.93E-33	3.91E-29

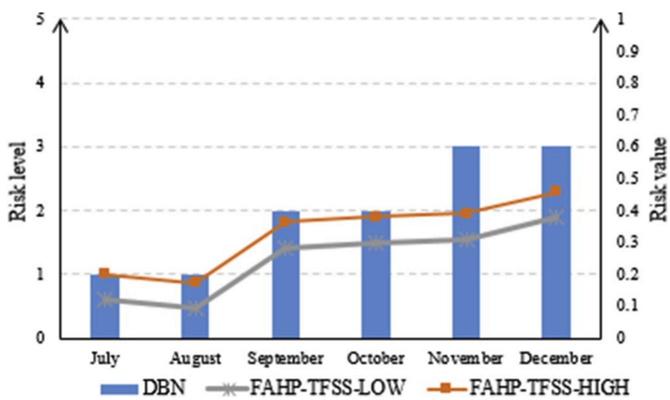

Fig. 6. Comparison results of two evaluation models in NO.1 node.

6.2. *Comparative analysis of Bayesian Network*

In order to test the rationality of considering the time term in this paper, the BN-model is obtained by removing the transfer network based on the network structure of Fig. 4. and the natural environment risk is comprehensively evaluated. See Table 9 for the results of risk inference using the BN-model.

Comparison calculation results of the BN and DBN models are approximately similar in describing the trends of the natural environment comprehensive risks of NO.1 node. However, the evaluation results of DBN-model are more obvious due to the accumulation of information. This is because DBN's reasoning effectively saves and accumulates experience and knowledge previously learned. Therefore, over time, more evidence and effective information is obtained. This implies that the DBN-model significantly improves the reasoning accuracy and reduces the uncertainty of reasoning effectively.

6.3. *Dynamic Bayesian Network model updating reasoning forecast experiment*

Assuming that the above-mentioned risk factor data for July to December are obtained through medium-and long-term numerical prediction reporting products, with the reduction of uncertainty factors, the numerical products update and revise the data of various impact factors in September 2016, as shown in Table 10. The DBN-model is used to evaluate and reason a single time slice in September. According to the principle of classification based on the maximum probability, the calculation results show that the natural environment state is still 'Low-risk', which are highly consistent with the previous results. The corresponding results are shown in Table 11.

Table 10
Update of evaluation index data in September 2016.

Indicator variable		d1	d2	d3	d4	d5
State update	Original forecast	4	2	1	2	5
	Revised forecast	3	2	4	2	4

Therefore, this experiment shows that DBN-model can still draw a highly reliable evaluation conclusion in combination with historical environmental information due to its information accumulation ability when errors occur in observation data. Simultaneously, the probability of 'high-risk' natural environment state increases following an update of the information. However, the probability of 'low-risk' decreases with changes of the environmental factors. This validates that DBN-model has high fault tolerance and strong update capability based on information detection, and can realize real-time or quasi-real-time assessment of natural environment risks, which is often impossible to realize in previous assessment methods.

7. Discussion

Taking NO.1 node of Ba-Lan key area as an example, the structure and parameters of DBN-model are conducted using expert experience and training sample set, and reasoning calculation is carried out based on the evidence set. Results show that the evaluation model can effectively deal with the fusion and reasoning of uncertain information, realize dynamic evaluation based on expert knowledge and objective data. In addition, it combines prior information and updates evidence information, consider the time of accumulation of information, and has better accuracy and fault tolerance However, this study has the following limitations:

(1) The natural environment safety risk index system of key nodes has insufficient index coverage. For instance, the navigation risk of the navigation channel may be affected by natural factors such as waves, currents and sea ice types. Therefore, the constructed index system in this study is not comprehensive, hence, requires further improvements.
(2) We used the modeling ideas of OOBN for reference, and explored in detail the risks of the natural environment modules. However, the status of ship and human error modules are not fully analyzed, therefore; more research should be conducted to address these aspects.

Table 9
BN reasoning results of NO.1 node.

		Time slice					
Comprehensive risk of natural environment in node NO.1	Risk level	July	August	September	October	November	December
	Lower risk	**0.7876**	**0.9270**	0	0	0	0
	Low risk	0.2124	0.0730	**1**	**0.9245**	**0.5158**	0.1206
	Medium risk	0	0	0	0.0755	0.4841	**0.8794**
	High risk	0	0	0	0	0	0
	Higher risk	0	0	0	0	0	0

Table 11
Evaluation results before and after the update of indicator data.

Scene	Higher risk	High risk	Medium risk	Low risk	Lower risk	Evaluation result
Original forecast	7.92E-32	3.96E-17	3.91E-07	**0.9999**	1.80E-08	Low risk
Revised forecast	1.37E-31	6.86E-27	1.56E-06	**0.9999**	9.65E-09	Low risk

(3) DBN itself is also a causal-reasoning model, so we will also learn from the excellent research results of C-RISE to analyze the probability distribution of risk factors from the perspective of accidents (results).

8. Conclusions

(1) This study uses the available data and previous milestones to establish a natural environment risk index system for safety assessment in key nodes of the Northwest Passage comprising of five indexes (gale risk, visibility risk, sea ice thickness risk, sea ice density risk and sea temperature risk).
(2) According to the multi-year (2005–2016) climate average of each index from July to September calculated and historical route data, we selected five key nodes in Ba-Lan key navigation area (73.5 °N-74.5° N, 90 °W-75° W) as the main research object.
(3) Taking the NO.1 node as an example, the evaluation results indicate that the comprehensive risk of the natural environment increased monthly from July to December. The risk was smallest between July to August making it the best airworthiness period.
(4) In comparison with FAHP-TFSS and BN models, the DBN-model objectively realizes the fusion and dynamic reasoning of multi-source environmental information. Over time, more evidence and information are obtained, therefore; the DBN-model significantly improves reasoning accuracy and effectively reduces the uncertainty of reasoning.
(5) By updating the reasoning prediction experiment, DBN-model can still provide highly reliable evaluation results when combination with historical environmental information. Moreover, the probability of some risk levels is adjusted according to the changes of risk factors. This verifies that DBN-model has strong updating ability, and can realize real-time or quasi-real-time assessment of natural environment risks.

Formatting of funding sources

This work has received funding from the Chinese National Natural Science Fund under grant agreement number 41976188.

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.

CRediT authorship contribution statement

Heng Qian: Conceptualization, Methodology, Software, Writing - original draft, Data curation. **Ren Zhang:** Writing - review & editing. **Yao-jia Zhang:** Supervision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.oceaneng.2020.107205.

References

Abbassi, R., Khan, F., Khakzad, N., Veitch, B., Ehlers, S., 2017. Risk analysis of offshore transportation accident in arctic waters. Int. J. Marit. Eng. 159, A213–A224.
Advisory, A.B.S., 2009. Low Temperature Operations-Guidlines for Arctic Shipping. ABS, Houston, TX.
Advisory, A.B.S., 2014. Navigating the Northern Sea Route. ABS, Houston, Texas.
Afenyo, M., Khan, F., Veitch, B., Yang, M., 2017. Arctic shipping accident scenario analysis using Bayesian Network approach. Ocean. Eng. 133, 224–230.
Afenyo, M., Khan, F., Veitch, B., Ng, A.K., Sajid, Z., Fahd, F., 2019. An explorative object-oriented Bayesian network model for oil spill response in the Arctic Ocean. Safety Extreme Environ. 1–12.
Bai, C.J., Li, Z.H., Yang, Z.C., 2009. Discussion on arctic routes. Navi. Technol. 5, 7–9.
Baksh, A.A., Abbassi, R., Garaniya, V., Khan, F., 2018. Marine transportation risk assessment using Bayesian Network: application to Arctic waters. Ocean. Eng. 159, 422–436.
Barua, S., Gao, X., Pasman, H., Mannan, M.S., 2016. Bayesian network based dynamic operational risk assessment. J. Loss Prev. Process. Ind. 41, 399–410.
Borgerson, S.G., 2008. Arctic meltdown-The economic and security implications of global warming. Foreign Aff. 87, 63.
Bowditch, N., 2002. The American Practical Navigator: an Epitome of Navigation and Nautical Astronomy. National Imagery and Mapping Agency, Bethesda, Maryland.
Canadian Coast Guard, 2012. Ice Navigation in Canadian Waters. Ice Breaking Program. Maritime Services, Canadian Coast Guard, Fisheries and Oceans, Ottawa.
arXiv Cussens, J., 2012. Bayesian Network Learning with Cutting Planes. arxiv: 1202.3713.
Dan, W., Jie, W., Hao, Z., 2015. Study of arctic waterway transit policy and its development on circumpolar nations and regions. Chin. J. Polar Res. 27, 74–82, 01.
Dean, T., Kanazawa, K., 1989. A model for reasoning about persistence and causation. Comput. Intell. 5, 142–150.
Environment Canada, 2016. Environment and climatic change Canada. January 15. Accessed February 5, 2017. https://www.ec.gc.ca/glaces-ice/default.asp?lang=En&n=501D72C1-1&def=hide1B3B2F69A.
Feng, J., Li, I., Pei, Y., Xiao, F., et al., 2012. Application of Dynamic Bayesian Network in target selection of communication countermeasure. Electronics Optics & Control.
Ferdous, R., Khan, F., Veitch, B., Amyotte, P.R., 2009. Methodology for computer aided fuzzy fault tree analysis. Process Saf. Environ. Protect. 87 (4), 217–226.
Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., Veitch, B., 2013. Analyzing system safety and risks under uncertainty using a bow-tie diagram: an innovative approach. Process Saf. Environ. Protect. 91 (1–2), 1–18.
Fu, Q., 2012. Research on the Variation of Ice Condition in the Key Areas of Northwest Passage. Dalian Maritime University, pp. 25–35.
Fu, S., Zhang, D., Montewka, J., Yan, X., Zio, E., 2016. Towards a probabilistic model for predicting ship besetting in ice in Arctic waters. Reliab. Eng. Syst. Saf. 155, 124–136.
Murphy, K.P.. FullBNT-V1.0.4. Accessed June 3, 2018. https://download.csdn.net/download/b08514/6942975.
Howell, S.E.L., Duguay, C.R., Markus, T., 2009. Sea ice conditions and melt season duration variability within the Canadian Arctic Archipelago: 1979-2008. Geophys. Res. Lett. 36, L10502.
Huang, D., Chen, T., Wang, M.J.J., 2001. A fuzzy set approach for event tree analysis. Fuzzy Set Syst. 18, 153–165.
Huang, Y., Ying, Y., Ji, Y., 2008. Optimization of Supply Chain Partner Based on VIKOR Method and G1 Method[C]//International Seminar on Future Biomedical Information Engineering.
Jie, S., Dong, X., Jinping, Z., Xiang, L., 2010. Features of North West Passage sea ice's distribution and variation under Arctic rapidly warming condition. Chin. J. Polar Res. 22 (2), 104–124.
Jin, J.L., Fan, Q.Y., Zhang, M., et al., 2009. Economic risk analysis method of flood control engineering system based on stochastic simulation of triangular fuzzy numbers. In: International Conference on Chinese Control & Decision Conference, 27, pp. 74–82, 01.
Jin, J.L., Liu, L., Wang, M.W., et al., 2011. Comprehensive risk assessment model for groundwater environment system based on triangular fuzzy number stochastic simulation. Geo. Sci. 31, 143–147, 02.
Jin, J.L., Wei, Y.M., Zou, L.L., et al., 2012. Risk evaluation of China's natural disaster systems: an approach based on triangular fuzzy numbers and stochastic simulation. Nat. Hazards 62 (1), 129–139.
Jing, L., Yao, W., 2013. A safety assessment of China's crude oil import based on G1 method. Proc. Soc. Behav. Sci. 96, 1738–1744.
Kalantarnia, M., 2009. Dynamic Risk Assessment Using Accident Precursor Data and Bayesian Theory. Doctoral dissertation. Memorial University of Newfoundland.
Khakzad, N., Khan, F., Amyotte, P., 2011. Safety analysis in process facilities: comparison of fault tree and Bayesian network approaches. Reliability Eng. Proc. Safety 96, 925–932.
Khakzad, N., Khan, F., Amyotte, P., 2012. Risk-based design of process systems using discrete-time Bayesian networks. Reliab. Eng. Syst. Saf. 109, 5–17.

Khan, F., Yang, M., Vetch, B., Ehlers, S., Chai, S., 2014. Transportation risk analysis framework for Arctic waters. In: Proceedings of the ASME 2014 33rd International Conference on Ocean, Offshore and Arctic Engineering. OMAE2014. ASME, San Francisco, CA. June 8-13, 2014.
Khan, B., Khan, F., Veitch, B., Yang, M., 2018. An operational risk analysis tool to analyze marine transportation in Arctic waters. Reliab. Eng. Syst. Saf. 169, 485–502.
Khon, V.C., Mokhov, I.I., Latif, M., et al., 2010. Perspectives of northern sea route and northwest passage in the twenty-first century. Climatic Change 100 (3–4), 757–768.
Kjaerulff, U., 1995. A computational system for dynamic time-sliced Bayesian networks. Int. J. Forecast. 11, 89–101.
Kum, S., Sahin, B., 2015. A root cause analysis for Arctic marine accidents from 1993 to 2011. Saf. Sci. 74, 206–220.
Lauritzen, S.L., 1995. The EM Algorithm for Graphical Association Models with Missing Data. Elsevier Science Publishers B. V.
Li, Z., 2016. Impact of Using the Arctic Passage on China's Economic Interest: Trade Potential and its Influence on Economic Growth. Shanghai Ocean -University, pp. 2–16.
Li, M., Liu, K., 2018. Application of intelligent dynamic bayesian network with wavelet analysis for probabilistic prediction of storm track intensity index. Atmosphere 9 (6), 224.
Li, Z.F., Liu, B.H., Xu, M.Q., 2012. An evaluation of the arctic route's navigation environment. In: Advanced Materials Research, vol. 518. Trans Tech Publications, pp. 1101–1108.
Li, Q., Shi, Y., Chen, Z., Zheng, C., Sun, X., 2018. Damage assessment model of civil airfield in an air raid based on dynamic bayesian network. Dandao Xuebao/Journal of Ballistics 30 (1), 93–96.
Liu, P., Zhang, X., 2011. Research on the supplier selection of a supply chain based on entropy weight and improved ELECTRE-III method. Int. J. Prod. Res. 49 (3), 637–646.
Lu, B.G., 2012. Environmental Factors in the Arctic Navigation and Safety Measures in the Ice Area. Dalian Maritime University, pp. 1–34.
Maritime Administration of the People's Republic of China, 2016. Guide to Arctic Navigation. Northwest Passage: 2015. People's Communications Press Co., Ltd., Beijing, pp. 240–260.
McNaught, K.R., Zagorecki, A., 2010. Using dynamic Bayesian networks for prognostic modeling to inform maintenance decision making. In: The IEEE International Conference on Industrial Engineering and Engineering Management (Hong Kong).
Montani, S., Portinale, L., Bobio, A., 2005. Dynamic Bayesian networks for modeling advanced fault tree features in dependability analysis. In: Kolowrocki (Ed.), Advances in Safety and Reliability. Taylor and Francis Group.
Pauplin, O., Jiang, J., 2012. DBN-based structural learning and optimisation for automated handwritten character recognition. Pattern Recogn. Lett. 33 (6), 685–692.
Pharand, D., 2007. The arctic waters and the Northwest Passage: a final revisit. Ocean Dev. Int. Law 38 (1–2), 3–69.
Rothblum, A.R., 2000. Human Error and Marine Safety. National safety council congress and expo.
Sahin, B., Kum, S., 2015. Risk assessment of Arctic navigation by using improved fuzzy-AHP approach. Int J Maritime Eng 157 (Part A4), 2015.
Shan, Y.L., Zhang, R., Li, M., et al., 2019. Generation and analysis of gridded visibility data in the arctic. Atmosphere 10 (6), 314.
Sou, T., Flato, G., 2009. sea ice in the Canadian arctic Archipelago: modeling the past (1950-2004) and the future (2041-2060). J. Clim. 22, 2181–2198.
Stephens, H., 2016. The opening of the northern sea routes: the implications for global shipping and for Canada's relations with Asia. SPP Research Paper No 9 (19).
Straub, D., 2005. Natural hazards risk assessment using Bayesian networks. In: 9th International Conference on Structural Safety and Reliability (ICOSSAR 05).
Wang, M., Chen, G., 2010. Coupling risk model of set pair analysis and stochastic simulation of triangular fuzzy numbers for the evaluation of shrink and expansion of the expansive soil. In: Seventh International Conference on Fuzzy Systems & Knowledge Discovery.
Wei, Q., Li, I., Jian, C.X., et al., 2010. Application of dynamic bayesian networks in hydrologic forecast. Comp. Eng. Appl. 46 (6), 231–234.
Xie, G.Q., 2014. Study on the Navigation Environment and Safe Navigation of the Northeastern Arctic Channel. Dalian Maritime University, p. pp274.
Yang, L.Z., Zhang, R., Ge, S.S., et al., 2013. Natural environment risk assessment of Northwest Passage based on climate change. Ann. Meet. Chinese Meteorol. Soc. 10–15.
Yi, W., Yuan, S., Li, J.Y., et al., 2012. Air Defense Threat Assessment Based on Dynamic Bayesian Network. Computer Technology & Development, pp. 721–724.
Yu, Y., Ding, Y., 2014. Improved Dynamic Bayesian Networks in Sea-Battlefield Situation Assessment. Trans Tech Publications.
Zeng, Z., Zio, E., 2018. Dynamic risk assessment based on statistical failure data and condition-monitoring degradation data. IEEE Trans. Reliab. (99), 1–14.
Zhang, D., 2014. Challenges and new developments in maritime risk assessment. In: Proceedings of the Probabilistic Safety Assessment and Management (PSAM) 12 Conference. CreateSpace Independent Publishing Platform, Honolulu, Hawaii.
Zou, L., Huang, S., 2016. A comparative study of the administration of the Canadian Northwest Passage and the Russian northern sea route. Asian Countries and the Arctic Future 121–141.