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Analysis of factors affecting the severity of marine accidents using a data-driven Bayesian network

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Abstract

A data-driven Bayesian network model (BN) is used to analyze the relationship between the severity of marine accidents and relevant Accident Influential Factors (AIFs). Firstly, based on the marine accident investigation reports involving 1,294 ships from 2000 to 2019, the severity grades of marine accidents are classified, and a database of factors affecting the severity of marine accidents is established. Secondly, a Tree Augmented Naive Bayesian algorithm (TAN) is used to establish a data-driven BN model, and the established database of AIFs is analyzed by data training and machine learning to reveal the influence of related factors on the severity of the accident and the mechanism of action. Finally, the sensitivity analysis and verification of the model are conducted. Through the analysis of the Most Probable Explanation (MPE), it explains the possible configurations in different scenarios and identifies the related potential risks. This study finds that "accident type" and "ship type" are the two most important AIFs of three accident severity grades, "capsizing/sinking", "hull/machinery damage" and "collision" that are most likely to lead to very serious accidents. Further, the possibility of fishing boats or other small ships leading to "very serious accidents" is also higher than that of other types of ships. The results of this study can help analyze and predict marine accidents and ensure the safe navigation of ships and hence benefit such maritime stakeholders as safety authorities and ship owners.

Keywords: Maritime safety, Marine accidents, Accident severity, Bayesian networks, TAN network

1. Introduction

Identifying and exploring the influential factors of marine accidents and incidents have always been one of the key research directions in the shipping industry (Rawson and Brito, 2022). The growth of international trade makes the number of ships increased and maritime traffic density higher, which results in a higher chance for a ship involved in a marine accident (e.g. collision), particularly in restrict waters. According to the 2021 Transport Industry Development Statistics Bulletin published by the Ministry of Transport, China in May 2022, there were 129 ship accidents in China in 2021, resulting in 153 deaths and missing persons (MoT, 2022). Meanwhile, the European Maritime Safety Agency (EMSA) reported in its annual accident statistics published in December 2021 that there were 22,532 marine accidents between 2014 and 2020, resulting in 8,015 ships suffering from loss or damage of varying degrees and 6,921 injuries (EMSA, 2021). In addition, Allianz Global Enterprise & Special Risks (AGESR) reported in its annual report in 2022 that there were about 3, 000 marine accidents in 2021 (AGCS, 2022).

As the development of computing methods and their applications in the study of accident mechanism, the investigation and research of marine accidents have achieved certain development. At present, according to the marine accident investigation reports of specific waters, some researchers obtained corresponding research results based on the causes and results of marine accidents, by using different mathematical and statistical methods (Acharya et al., 2017; Ceylan et al., 2021; Fan et al., 2020a; Kaptan et al., 2021; Navas de Maya and Kurt, 2020). According to existing studies, factors influencing the occurrence of marine accidents are usually divided into three categories: human factors, ship factors and environmental factors (Kaptan et al., 2021). However, according to the accident mechanism, human factors can be further classified into human and organizational factors (Hänninen et al., 2014; Wu et al., 2021; Zaccone and Martelli, 2020). It is found that although ships are equipped with many navigational aids equipment, human factors still have a critical impact on the probability and result of marine accidents, including the physical and mental state of sailors, theoretical knowledge level, communication and sense of responsibility (Coraddu et al., 2020). However, the determination of human factors is affected by certain subjectivity. When analyzing the result of accident severity, in addition to human factors, it is necessary to combine with other objective parameters for quantitative research (Wang et al., 2022). At the same time, some studies have found that there is a certain relationship between the severity of accidents and the ship's own parameters. For example, the severity of accidents caused by different ship types is specific, but often such results lack verification based on data analysis (Cakir et al., 2021a; Cakir et al., 2021b; Navas de Maya and Kurt, 2020). In addition, environmental factors and accident types, as important components in the process of accident occurrence, also have a certain impact on the severity of accidents (Xing et al., 2020). In general, there are still some limitations in previous studies on marine accidents. For example, previous studies focused more one frequency analysis or discussion of a specific type of accident, and few applications of data-driven methods in the research on the severity of marine accidents. Therefore, based on the database of 7 widely applied marine investigation agencies worldwide, this study collects the marine accident investigation reports of 1,294 ships and establishes the database of factors affecting the severity of accidents. Combined with the expert knowledge, the risk factors affecting the severity of marine accidents are screened, and the TAN-BN model is established by a data-driven method. Then the data training and processing are carried out, the sensitivity and effectiveness of the model are analyzed, and the factors affecting the accident severity are comprehensively analyzed for accident prevention.

The main research contents of this study are organized as follows. The second section mainly introduces the relevant factors affecting the marine accidents in the relevant literature and discusses the applications of BN in the investigation of marine accidents. The third section extracts relevant factors affecting the occurrence of marine accidents based on the marine accident investigation reports involving 1,294 ships from 2000 to 2019, establishes an influential factors database of marine accident, classifies the degree of accident severity, and introduces the naive Bayes algorithm in a BN model. At the same time, the method of model sensitivity analysis and the process of model verification are proposed. In the fourth section, the data after the model training and processing is analyzed and discussed, and the relevant influential factors with strong correlation to the severity of the accidents are studied, and the implications are drawn and revealed. Finally, the fifth section summarizes this study.

2 Literature review

2.1 Maritime accident related studies

With the continuous development of marine accident investigation technology and research, the analysis and judgment of the influential factors of accidents have also made significant progress. Galieriková (2019) pointed out that human factors are characterized by unpredictability, diversity and complexity, which can be preliminarily divided into three aspects: knowledge, rules and skills. On this basis, relevant researchers have made a more detailed classification of human factors. Among them, Fan et al. (2020b) analyzed that effective information, clear order and good safety culture were the most effective human factors to prevent accidents by using Technique for Preference by Similarity to Ideal Solution (TOPSIS). Fan et al. (2020a) also pointed out that different human factors are also associated with different types of marine accidents. For example, the occurrence of collision accidents is more likely to be caused by the lack of supervision of navigational officers, and the unsound safety management system is more likely to cause man overboard. At the same time, Chauvin et al. (2013) analyzed collision accidents and concluded that unsafe behaviors of navigational officers, such as mis-operation and violation of regulations, should also be taken into account in the human factors. Among them, the frequency of incorrect decisions and inappropriate operation instructions reached 25.6% and 16%, respectively. This also shows that individual crew members play a very important role on the occurrence of accidents. Coraddu et al. (2020) and Zhang et al. (2020) proposed the human factors of marine accidents, such as sailors' physical and psychological state, educational background, drill and training, which further enriched the current research.

Ship factor is also one of the important variables affecting marine accidents. Due to the unsafe nature of fishing ships and the characteristics of accident susceptibility, Jin (2014) found that stability is a key factor determining the severity of fishing ship accidents through the study of relevant accident data in the east coastal areas of the United States. When a ship loses stability, the possibility of total loss reaches 66.8%. Meanwhile, Navas de Maya and Kurt (2020) studied the accidents of bulk carriers, and analyzed the similarities and differences of different accidents of this type of ship. In the study of Cakir et al. (2021a), tugboat was mainly analyzed, and more than half of the accidents were hull damage, mechanical failure and collision. In the study of passenger ships, Yip et al. (Yip et al., 2015) and Rahman (2017) revealed that most passenger ship accidents are caused by non-standard operation and hull structure problems, and the severity of accidents (especially casualties) was related to the behavior of crew members. In addition, some researchers also conducted further research on the causes of marine accidents of autonomous cargo ships (Zhang et al., 2020), Ro-Pax ships (Wu et al., 2021), cruise ship (Talley et al., 2008) and tugboats (Cakir et al., 2021a) from different perspectives. Puisa et al. (2018) and Yang et al. (2018) analyzed the impact of onboard equipment, operating procedures and Port State Control (PSC) inspection on the severity of the accidents, respectively, and explored the correlation between the severity of the accidents and other ship factors.

Environmental factors belong to another category of the main factors affecting marine accidents. In the annual report issued by AGESR, it is noteworthy that extreme weather and complex fairway conditions were always the important factors affecting the safe navigation of ships (AGCS, 2022). By analyzing the M/V Sea Prince accident near South Korea, Cho (Cho, 2007) elaborated the harm caused by typhoons to the safe navigation of ships. In the situation of poor visibility during navigation, Bye and Aalberg (2018) found that low visibility would lead to ship navigation equipment failure, thus increasing the possibility of accidents. Weng and Yang (2015) and Chen et al. (2019) found from the investigation of casualties of marine accidents that the probability of serious accidents in waters far from ports or coastal areas is significantly higher than others, especially at the boundary of multi-country waters, and the possibility and severity of accidents will be higher. In addition, some researchers have analyzed and studied the accidents occurring in many specific sea areas around the world, such as the Yangtze River (Zhang et al., 2013), polar seas (Xue et al., 2021) and the Chinese coastal areas (Liu et al., 2021), provided a guarantee for the safe navigation of ships in different navigation areas. At the same time, Deng et al. (2021) analyzed the coupling effect of multiple factors according to the characteristics of different accidents, and found that, except for fire or explosion accidents, environmental factors have obvious influence on other types of accidents, and with the increase of the proportion of environmental factors involved, the severity of related accidents will increase accordingly.

Although the above studies have analyzed the influential factors of marine accidents from different perspectives, there are still some limitations in the data processing process. On the one hand, due to the complexity of multi-factor data processing, and the uncertainty and relevance of the relationship between factors, most studies only analyze single or few influential factors, and the existing studies fail at large to take into account the diversity and comprehensiveness of influential factors. On the other hand, there is no previous studies in the field that use seven databases to address accident data deficiencies. This study pioneers the contraction of the most comprehensive maritime accident database to analyse the parameters to a very detailed level by reducing uncertainty in data.

2.2 BN modelling applied to maritime accident analysis

In the maritime safety research, relevant researchers use a variety of methods to analyze marine accidents, and the classical analysis techniques include an ordered logistic regression model (Chen et al., 2019; Wang et al., 2021; Weng and Yang, 2015), System Theoretical Accident Model (STAMP) (Ceylan et al., 2021; Tang et al., 2019), Event Tree Analysis (ETA) (Galieriková, 2019; Navas de Maya and Kurt, 2020; Talley et al., 2008; Xue et al., 2021) and Bayesian networks (BN) (Fan et al., 2020a; Hänninen, 2014; Hänninen et al., 2014; Wang and Yang, 2018; Wu et al., 2021). BN has the advantages of learning and inference algorithms, it mainly extracts random variables involved in a study, and then draws a directed graph according to whether they are independent, which is used to describe the dependence relationship between the variables and express the conditional probability of events. In the process of marine accident analysis and research, BN can combine historical data and expert knowledge to establish a network structure, infer accident causes and predict accident results, so as to improve marine safety management and make the correct decision (Hänninen et al., 2014).

When studying the influence of human factors on marine accidents, Fan et al. (2020a) established a two-level risk influential factor database which containing 25 variables and used a BN structure to conduct parameters learning. In the study of ship navigation risks in the Arctic region, Li et al. (2021) and Baksh et al. (2018) selected 24 and 36 basic factor nodes to establish a risk inference network respectively, solved the problem of ship collision prediction in the ice area. Aiming at the safe navigation of ships in inland waterways, Zhang et al. (2013) and Zhao et al. (2021) extracted the relevant factors affecting the marine accidents in inland waterways. After establishing the corresponding database of key influential factors, a BN network was used to process the data. It was found that passenger ships, tugs and oil tankers in inland waterways are more likely to have serious accidents, and grounding is the most difficult accident to deal with. Deng et al. (2021) and Liu et al. (2021) analyzed accident investigation reports in coastal areas and reasoned through BN. It was found that small bulk cargo ships in coastal areas were more likely to have collision accidents, while severe weather conditions and high traffic density would aggravate the severity of accidents.

Based on the advantage of data-driven, BN has a good application in marine accident analysis. Li and Tang (2019) used BN to determine the impact of hull structure changes on the grounding of LNG ships. In addition, Jiang et al. (2020) used a BN structure to conduct simulation demonstration, and the results showed that the severity of ship collision accidents and hijacking events would greatly increase. In addition, the study also found that container ships and ships sailing close to offshore are relatively safer, which was also same as the results of Liang et al. (2022) and Dinis et al. (2020). Wu et al. (2021) analyzed the fire issue in the process of transporting electric vehicles on Ro-Pax ships by using BN combined with the maximum expectation algorithm, and found that the charging state and high external temperature would greatly increase the probability of accidents. Tang et al. (2019) used BN combined with a random forest technology to predict the factors causing different grades of collision accident in the Jiangsu section of the Yangtze River. Afenyo et al. (2017) focused on the analysis of the collision accidents in the ice area, established the event tree of iceberg collision by using BN, and proposed that the allocation of resources and investment was the key factor to prevent accidents, and the structure of BN also well reflected the conditional probability of various variables. It helps to make adjustments according to their prediction results, which is also corresponding to the results of Hänninen and Kujala (2014). In addition, Zhao et al. (2021) aiming to analyse the safety of maritime autonomous sea ship (MASS) via a BN model based on accident data in Yangtze river revealed that the intelligent development of ships will effectively reduce the collision and grounding accidents, but at the same time, fire or extreme weather can cause more serious consequences to MASS, which reminds the relevant stakeholders on the new safety problems when promoting the development of MASS in inland waters. Guo et al. (2023) developed a new dynamic BN model to analyse the risk evolution of ship pilotage operations, stimulating the BN applications in maritime accidents from both static and dynamic perspectives.

An extensive literature analysis has shown that the current research of severity of marine accidents is mostly for the verification and discussion of a single index, lack of database support, and fail to comprehensively analyze the coupling effect of multiple influential factors, and there are few applications of BN in the severity analysis of marine accidents. Combined with the above analysis, it can be found that BN has been widely used in the field of marine accident analysis, and the advantages of its learning and inference function can make it process more data and enhance the reliability and stability of the results. Therefore, this study aims to extract the accident risk influential factors from a large number of marine accident investigation reports, establish a comprehensive accident influential factors database, combine it with the expert knowledge for the classification and interpretation of the related factors, use a TAN-BN model to learn and train the database, analyze the factors affecting the accident severity, and enrich the study of marine accident severity.

3. Methodology

3.1 Research data

After the occurrence of a marine accident, the marine investigation agency obtains the basic information of the ship and the navigation data before and after the accident through various ways, (e.g., interviewing the surviving crew and passengers, checking the log and engine log records, and extracting the data of the voyage data recorder on board) to form the marine accident investigation report. Considering the integrity, reliability and openness of data, the Australian Transport Safety

Board (ATSB), Federal Bureau of Investigation Marine Accident Investigation Unit (BSU), China Maritime Safety Administration (China MSA), National Safety Transportation Board (NTSB), Canadian Transportation Safety Board (TSB), Marine Accident Investigation Branch (MAIB) and Japan Transportation Safety Board (JTSB), are used as the main data sources in this study.

The analysis of the marine accident investigation reports find that the details of accident records is different, and some data are inaccurate and/or incomplete. Therefore, accident records with incomplete data need to be eliminated, such as those that do not list the consequences of the accidents. After filtering the accident records, 2,513 accident records were obtained initially. Since the ships or crew may be involved in multiple countries, the accident investigation is conducted in the form of joint investigation, and each country concerned publishes investigation reports after the accident investigation, therefore this study further screens accident investigation reports and eliminates duplicate accident investigation reports. Finally, the database established in this study includes 1,294 marine accident investigation reports from 2000 to 2019. Fig. 1 shows the source distribution of marine accident investigation reports.

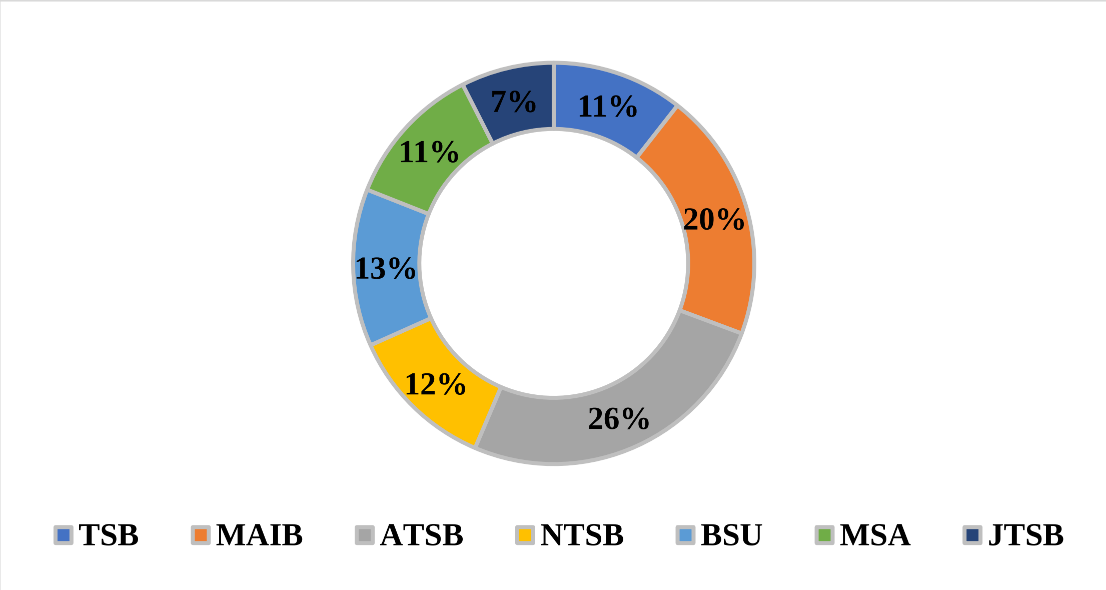

Fig. 1. Source distribution of water traffic accident reports.

At present, the International Maritime Organization (IMO) classifies the severity of marine accidents according to the degree of damage to the ship, casualties and environmental pollution (IMO, 2000). In addition, some countries have also classified the severity of accidents into different grades. For example, China classifies marine accidents into especially major accidents, serious accidents, major accidents and general accidents according to the damage consequences (MoT, 2014). According to the different severity classes of accidents, the UK divides them into three categories: especially serious marine accidents, major marine accidents and marine incidents (National, 2005). Through comparative analysis, IMO and most national marine investigation agencies have similar classification principles of marine accident severity. At the same time, considering that the database used in this study comes from the accident investigation reports of various countries, in order to ensure the consistency in the analysis process, this study classifies the severity of marine accidents into three categories according to the IMO classification standards. The specific grades and explanations are shown in Table 1 **Severity grade of marine accidents**.

Table 1 Severity grade of marine accidents.

No	Grade of severity	Notation	definition
1	Less serious casualties and marine incidents	S_1	There are no injuries, environmental pollution or minor hull damage.
2	Serious casualties	S_2	There are injuries, oil spills, or damage to the hull.
3	Very serious casualties	S_3	There are death or disappearance of persons, major oil spills or loss of ship in an accident.

3.2 Data pre-processing (Identification of AIFs)

Investigation reports are classified according to the established accident severity grades (i.e., Table 1). Based on the relevant literature (Wang et al., 2021; Wang and Yang, 2018), this study extracts human, ship and environmental factors as the first-level indexes of AIFs database. Through further analysis, it is concluded that the main body causing the existence of human factors is the crew involved in the accident. For example, the physical and mental state of the crew, the theoretical knowledge level and communication ability, the work experience and the standardization of operation all have an impact on the safe navigation of the ships. According to the analysis of ship factors, it can be found that the seaworthiness, safety feature and parameters of a ship are the second-level indexes that affect the severity of an accident. Among them, ship parameters include ship type, ship age, engine power and tonnage, and whether it is a flag of convenience. Ship seaworthiness includes the ship's certificate and personnel. Ship safety feature mainly refers to the PSC/FSC inspection before the accident. Environmental factors mainly consider the channel conditions and natural factors in the water area where the ship sailing. According to relevant researches (Deng et al., 2021; Xing et al., 2020) channel conditions include the location of the water area, water depth, channel width and navigable density, while natural conditions refer to wind, waves, currents and visibility (Wang et al., 2021; Wang et al., 2022).

In the process of data processing, this study will directly apply the existing unified classification, for example, the definition and classification of "accident type" and "ship type" appear in the accident report of MAIB and TSB, and this classification standard has also been widely used in the industry (Fan et al., 2020b). However, a careful review of all accident investigation reports reveals that the classification of accident influential factors by various marine investigation agencies is not completely consistent, and some information needs to be integrated and standardized. Among the human, ship and management factors, since the marine accident investigation report did not provide a unified definition of the state of AIFs "Physical & Psychological state", "education background", "Communication problem", "Operational Error" and "Violation Operation", "Seaworthiness", "Safety management system" and "Company Safety culture". Therefore, the relevant literature (Coraddu et al., 2020; Zhang and Thai, 2016) and expert knowledge were used to determine the specific status levels of the above factors. For AIFs with continuity characteristics, they can be divided into several independent subsets according to the classification standard of literature (Wang et al., 2021), such as "Time at sea", "Time in present rank ", etc. By discretizing, the continuous eigenvalues can be transformed into hierarchical state values, which is convenient for subsequent data processing and probability calculation.

After determining the third-level influential factor indexes by text analysis and expert judgment, this study establishes a database of influential factors of marine accident including 35 third-level AIFs. Meanwhile, in order to facilitate the data learning and probability calculation of BN in the next step, possible states of each AIF are assigned in this study, as shown in Table 2 **Database of influential factors of severity of marine accidents**.

Table 2 Database of influential factors of severity of marine accidents.

No.	Level I	Level II	Level III	Notation	Value/definition	Corresponding values
1	Accident	Accident type	Accident type	R_1	collision, stranding/grounding, fire/explosion, contact, capsize/sinking, hull/machinery damage, other	1,2,3,4,5,6,7
2		Date and time	Month	R_2	January, February, March, April, May, June, July, August, September, October, November, December	1,2,3,4,5,6,7,8,9,10,11,12
3			Time	R_3	0000-0400, 0400-0800, 0800-1200, 1200-1600, 1600-2000, 2000-2400	1,2,3,4,5,6
4	human	crew	Physical & Psychological state	R_4	poor, good	1,2
5			Education background	R_5	poor, good	1,2
6			Time at sea	R_6	< 5 years, 5 <= time < 10 years, >= 10 years	1,2,3
7			Time in present rank	R_7	< 1 year, 1 <= time < 5 years, >= 5 years	1,2,3
8			Communication problem	R_8	yes, no	1,2
9			Operational error	R_9	yes, no, unknown	1,2,3
10			Violation operation	R_{10}	yes, no, unknown	1,2,3
11	Ship	Ship particulars	Type	R_{11}	bulk carrier, container ship, oil tanker, passenger ship (including cruise and ro-ro passenger ship), chemical tanker, general cargo ship, fishing ship, yacht and sailing ship, tug and port traffic boat, others	1,2,3,4,5,6,7,8,9,10
12			Age	R_{12}	0-10 years, 10-20 years, 20-30 years, >= 30 years	1,2,3,4
13			Gross tonnage	R_{13}	< 500 t, 500-3000 t, >= 3000t	1,2,3
14			Engine power	R_{14}	< 750 KW, 750-3000 KW, >= 3000KW	1,2,3
15			Flag state	R_{15}	Flag of convenience, Not flag of convenience	1,2
16		Voyage data	Ship's certificates	R_{16}	complete and valid, incomplete or invalid	1,2
17			Ship manning	R_{17}	adequate, inadequate	1,2
18			Seafarers' certificates	R_{18}	complete and valid, incomplete or invalid	1,2
19			Seaworthiness	R_{19}	yes, no	1,2
20			PSC/FSC inspection	R_{20}	unsure, sure	1,2
21	Environment	External environment	Location	R_{21}	Inland waters, Port, Coastal waters, Open Sea	1,2,3,4

22			Visibility	R_{22}	very poor - Vis < 0.5 nm, Poor - 0.5 <= Vis < 2 nm, Moderate - 2 <= Vis < 5 nm, Good and very good - Vis >= 5 nm	1,2,3,4
23			Wind force	R_{23}	0-5, 6-7, 8-9, 10-12	1,2,3,4
24			Sea state	R_{24}	0-3, 4-5, 6-7, 8-9	1,2,3,4
25			Current speed	R_{25}	< 2 kn, 2-4 kn, >=4 kn	1,2,3
26		Navigational/ geographical condition	Traffic density	R_{26}	low, high	1,2
27			Fairway width/ship length	R_{27}	w/l < 1, 1<= w/l < 2, w/l >= 2	1,2,3
28			Depth-draft ratio (h/d)	R_{28}	h/d < 1.2, 1.2 <= h/d < 1.5, 1.5 <= h/d < 3, h/d >= 3	1,2,3,4
29	Management	Administration	Regulation	R_{29}	inadequate, adequate	1,2
30			Supervision	R_{30}	inadequate, adequate	1,2
31		Company	Safety management system	R_{31}	defective, non-defective	1,2
32			Rectification of problems	R_{32}	unresponsive, responsive	1,2
33			Company safety culture	R_{33}	poor, good	1,2
34		ship	Training	R_{34}	inadequate, adequate	1,2
35			Drill	R_{35}	off schedule, stick to the schedule	1,2

3.3 TAN-BN modelling

A BN is mainly composed of a directed acyclic graph (DAG) and associated probability distribution tables (Hänninen, 2014). Among them, nodes and directed edges form the DAG. Nodes represent random variables, which are usually labeled with variable names, and different state values can be determined according to their discretization or continuity. The directed edges between nodes represent the direct dependencies between connected variables, thus determining the statistical correlations between nodes and the conditional probability table (CPT). In this study, a large amount of statistical information is used to construct a complete CPT, which makes BN have good stochastic modeling ability and the ability to deal with nonlinear relations, and realizes the reasoning function under incomplete, imprecise and uncertain information.

There are many data-driven Bayesian methods, such as naive Bayesian network, Augmented Naive Bayesian network and Tree Augmented Naive Bayesian network (TAN). TAN improves naive Bayesian networks by structural extension, which preserves the learning ability of BN and avoids the complexity of studying Bayesian networks (Fan et al., 2020a; Friedman et al., 1997; Wang and Yang, 2018). Therefore, this study will use TAN to establish a TAN-BN model to analyze the influential factors of accident severity.

Firstly, the severity grade of marine accidents is coded, and "accident severity" is taken as class variable (S). The three accident severity grades in Table 1 are assigned to S, which are represented by "S_1", "S_2" and "S_3" respectively. Secondly, the third-level indexes in the data set of influential factors in Table 2 are taken as AIFs to establish the risk variable set R, and let $R = \{R_1, \dots R_{35}\}$. Finally, for a DAG, if class variable is regarded as the only parent node of each variable in set R, namely $\prod R_i = \{S\}, 1 \le i \le 35$, and the parent set corresponding to class quantity S is an empty set, that is, class variable S does not have a parent node, then the joint probability distribution formula defined in BN is shown in Eq. (1):

$$P(R_1, \dots R_{35}, S) = P(S) \cdot \prod_{i=1}^{n} P(R_i|S) \tag{1}$$

If R_i in all AIFs has only one parent in addition to the established class variable S, then the DAG is a tree, so a function π should also be defined in the set R to ensure that there are no loops in the tree structure. The condition for the function π to define a tree on R is that there exists one and only one i such that $\pi(i) = 0$, that is, each variable has only a unique parent, and there is no sequence $i_1, \dots i_k$, such that $\pi(ij) = i_{j+1}, i \le j < k$, and $\pi(i_k) = i_1$, that is to ensure that the acyclic structure appears. In this case, the function π defines a tree network, and when $\pi(i) > 0$ and $\prod R_i = \{S, \dots R_{\pi(i)}\}$, when $\pi(i) = 0$, $\prod R_i = \{S\}$. Therefore, when the TAN structure model conducts learning inference, the main process is to find a tree in the model and define the function π about the set R to maximize its log-likelihood value. In addition, the TAN structure also uses the calculation of conditional mutual information between variables in the learning and reasoning process, and the calculation process of mutual information is shown in Eq. (2):

$$I_P(R_i, R_j|S) = \sum_{r_{ii}, r_{ji}, S_i} P(r_{ii}, r_{ji}, S_i) log \frac{P(r_{ii}, r_{ji}|S_i)}{P(r_{ii}|S_i)P(r_{ji}, S_i)} \tag{2}$$

where I_P stands for conditional mutual information, r_{ii} stands for the i^{th} state of R_i in AIF, r_{ji} stands for the i^{th} state of R_j in AIF, S_i stands for the i^{th} grade of accident severity.

After determining the calculation method of mutual information I_P and joint probability P, the establish process of the TAN model is mainly divided into the following four steps (Yang et al., 2018):

(1) Based on the AIFs in Table 2, the corresponding node graph of all variables R_i is set up and

connected to complete the construction of the entire undirected graph. Each node graph contains the name of the variable and the corresponding number of each state, and the correlation degree between variables is determined by calculating the mutual information value between nodes.

(2) Establish a maximum weighted spanning tree. The main process is to ensure that there is no cycle in the tree structure according to the function π defined above, and to maximize its log-likelihood value.

(3) For the established undirected tree, the connection direction between the target node and the attribute variable is determined by using the calculated mutual information value.

(4) Add class variable S and establish directed connection with all variables R_i to complete the TAN modeling process.

3.4 Sensitivity analysis

3.4.1 Mutual information

Mutual information is a measure to describe the interdependence between variables, and can also be used as a standard for feature selection and feature transformation among variables in machine learning (Fan et al., 2020a). Therefore, when studying the relationship between influential factors and accident severity, "accident severity", as a class variable, can be determined by calculating the mutual information value between risk variables included in AIFs and "accident severity". The specific calculation process is shown in Eq. (3):

$$I(S, r_i) = -\sum_{S,i} P(S, r_{ij}) log \frac{P(S, r_{ij})}{P(S)P(r_{ij})} \tag{3}$$

where S represents the severity of an accident, r_i represents the i^{th} AIF variable, r_{ij} represents the j^{th} state of the i^{th} AIF, and $I(S, r_i)$ represents the mutual information value between the severity of the accident and the i^{th} AIF.

In this study, after establishing the TAN-BN model, calculating the mutual information value can be used to compare the relationship between a single AIF and "accident severity", that is, the greater the mutual information value, the stronger the relationship between the AIF and "accident severity". This method can screen the risk variables, filter out the AIF with relatively small impact, and reduce the workload of subsequent calculation.

3.4.2 Joint probability

Joint probability refers to the probability that contains multiple conditions and all conditions hold at the same time (Jiang et al., 2020). In this study, the TAN-BN model is used to assign corresponding probability values to different states of related AIFs. When other AIFs variables are locked, the probability distributions of different states of class variables or target nodes can be calculated. The sum of the joint distribution probability values corresponding to different states of an AIF is 1. The specific calculation process is shown in Eq. (4), where S represents the severity of the accident and R_{ij} represents the j^{th} state of the i^{th} AIF:

$$P(S, R_{ij}) = P(S) \cdot P(R_{ij}|S) \tag{4}$$

3.4.3 True risk influence

True Risk Influence (TRI) is a novel sensitivity verification method proposed by Alyami (2019). In the process of sensitivity analysis, AIFs with relatively greater impact are screened out through the mutual information value, and the TAN-BN model is used to calculate the high risk influence value (HRI) and low risk influence value (LRI) of these AIFs, and then the average value of the two, namely TRI, is calculated to determine the impact degree of a variable on the severity of the accident. The calculation process is divided into three steps:

(1) Increase the occurrence probability of the state that has the greatest impact on a certain accident severity grade in a variable node to 100%, obtain the occurrence probability of this accident severity grade at this time, and make the difference with the initial probability value to obtain HRI.
(2) Increase the occurrence probability of the state that has the least influence on the severity grade of an accident to 100% in a variable node, obtain the occurrence probability of the severity grade of the accident at this time, and make the difference with the initial probability value to obtain LRI.
(3) Calculate TRI by using the obtained HRI and LRI, and the specific process is shown in Eq. (5):

$$TRI = \frac{HRI + LRI}{2} \tag{5}$$

Therefore, in order to compare the influence degree of other relevant variable nodes on "accident severity", the TRI corresponding to each accident severity grade was calculated for all screened AIFs, and the TRI values of all variables on all accident severity grades are obtained, and the priority is arranged. Under this sensitivity analysis method, the greater the value of TRI, the greater the impact of the corresponding node on the "accident severity".

3.5 Model validation

Since axiom-based verification is widely used in BN, two axioms are used to verify the robustness of the model. To further ensure the validity of the model, receiver operating characteristic curve (ROC) and case analysis were used for model validation based on similar studies (Fan et al., 2020a; Guo et al., 2023; Wang and Yang, 2018; Yang et al., 2018).

3.5.1 Validation method 1 (2 Axiom)

Model validation is one of the important steps in the result analysis stage. In the process of sensitivity analysis, according to relevant literature (Jones et al., 2010; Zhang et al., 2013) , the TAN-BN model should satisfy the following two axioms:

Axiom 1: When the prior probability of each AIF slightly increases or decreases, the posterior probability of the target node should be increased or decreased accordingly.

Axiom 2: The total effect of the comprehensive probability change of x parameters should not be less than the total effect of the probability change of the set of y ($y \in x$).

3.5.2 Validation method 2 (ROC)

The sensitivity and accuracy of the established TAN-BN structure can be verified by drawing the receiver operating characteristic curve (ROC). The abscissa of this curve is the false positive rate and the ordinate is the true positive rate (Jiang et al., 2020). After the structure of the TAN-BN model is determined, the area under the curve (AUC) can be used to quantitatively analyze the performance of the model, and the value of AUC is generally between 0.5 and 1. The larger the value of AUC, the better the performance of this model is (Wang and Yang, 2018).

3.5.3 Validation method 3 (case analysis)

In order to further verify the reliability of the model, this study chooses a historical accident report which is not included in this study, and puts the known accident factors to the established TAN-BN model, and observe model of the output as a result. The result will be compared with the accident report to verify the veracity and reliability of the model.

3.6 Scenario analysis (MPE)

In order to observe the connections between related nodes in BN and find the most likely state of occurrence in a node, a BN model can provide the most likely explanation (MPE) based on the determined accident severity, which is also a special case of maximum posterior probability. By setting a state of class variable or target node as the MPE mode, the BN model can observe the most likely situation of other nodes under a certain accident severity, that is, the most likely AIF state, and predict the causes of marine accidents to a certain extent.

In the MPE mode, there is at least one 100% confidence bar in all states of each node, and the confidence bars of other states are at a lower level. The node state corresponding to the confidence bar at 100% level is the most likely situation, and the state at other levels represents the relatively low possibility of occurrence, and its probability value is the result after scaling. Some nodes also have multiple 100% level confidence bars, which means that the node states corresponding to these 100% level confidence bars are equally likely to appear under a certain accident severity grade.

4 Results and discussion

4.1 TAN-BN modelling

The structure learning of BN can be carried out from two steps: (1) establishing the relationship between variables based on data-driven method, and (2) analyzing and improving the established relationship structure based on expert knowledge. The relationship based on the data-driven method can be used to calculate the mutual information value to evaluate the correlation degree between variables. However, the structure established by this method has certain complexity, and the connections between some nodes may not be consistent with the actual situation (Fan et al., 2020a; Liang et al., 2022; Liu et al., 2021; Wang and Yang, 2018). Therefore, on the basis of machine learning and data training, this study further evaluates and improves the preliminarily established structure through expert evaluation, so that the final TAN-BN model has better robustness.

4.1.1 TAN-BN structure

According to the method in Section 3.3, the Netica software package (Norsys, https://www.norsys.com) is used as an auxiliary calculation tool, and the built-in "structure learning" function of the software is used, combined with Eq. (3), to establish the TAN-BN model as shown in Fig. 2. The TAN-BN model established in this study includes 35 AIFs in Table 2 and shows the relationship between the variables.

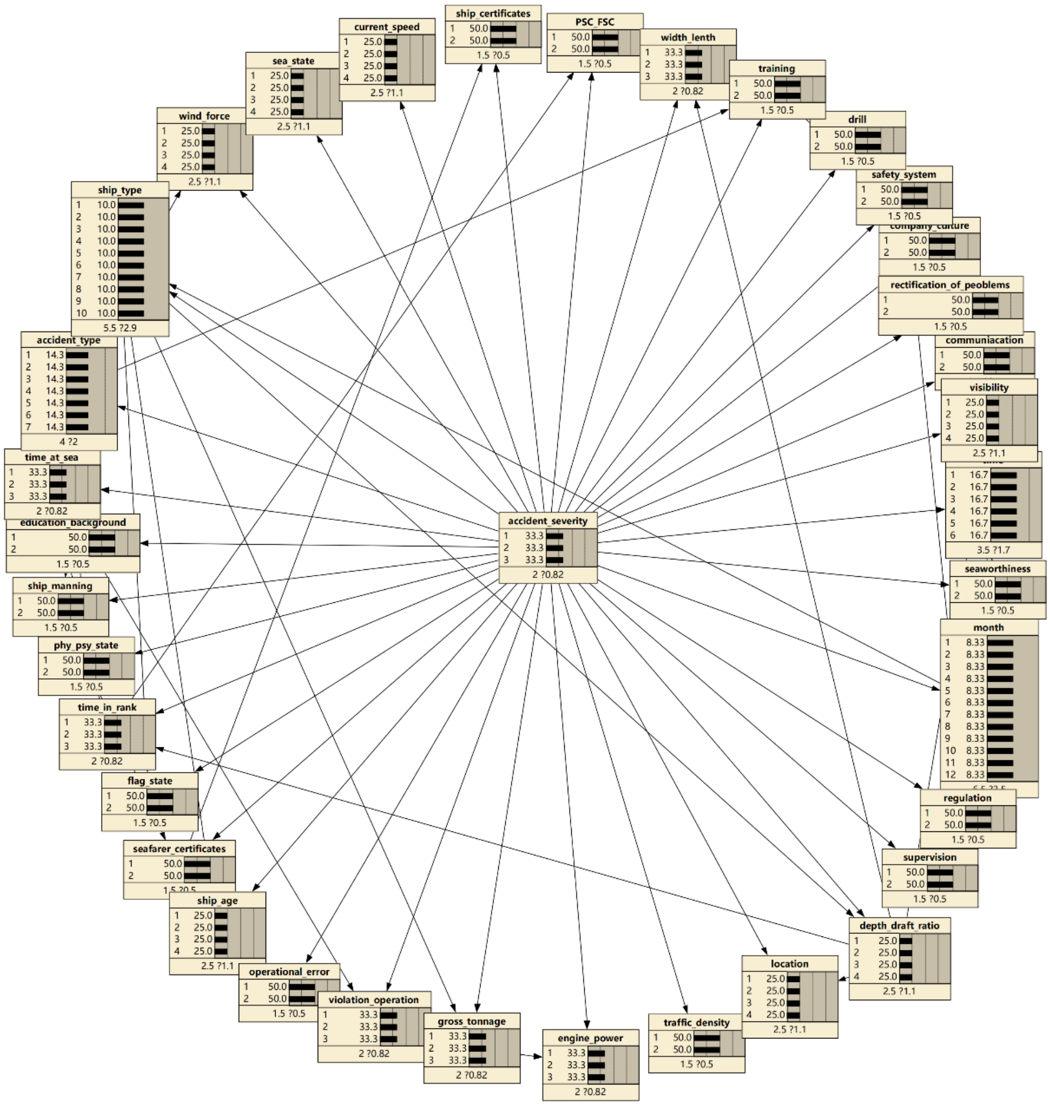

Fig. 2. TAN-BN model nodes.

4.1.2 Experts' knowledge

Fig. 2 shows the TAN-BN model preliminarily established based on the data-driven method. Subsequently, five experts in the field of marine accident analysis are invited to further evaluate the connections between the established model nodes. The basic information of these experts is shown in Table 3.

Table 3 The background information of the employed experts.

Expert No.	Age	Job Title	Field and Experience
Expert A	45	Officer of the Maritime Administration	Engaged in maritime supervision for 15 years
Expert B	38	Associate professor, second officer	Engaged in research related to marine accident analysis for 10 years
Expert C	35	Associate professor, third officer	Engaged in research related to ship safety for 8 years
Expert D	63	Chief officer and professor	Engaged in research related to maritime safety for 35 years
Expert E	47	Captain and associate professor	Engaged in theory and practice related to marine navigation for 21 years

According to the expert judgment, it can be found that the relationship between some nodes in the model (as shown in Fig. 2) does not conform to the actual situation. Therefore, the corresponding connections are deleted according to expert evaluation opinions, as shown in Table 4, and the TAN-BN model established in this study is finally obtained, as shown in Fig. 3.

Table 4 The deleted connections of some nodes.

Node	Linked node
Depth-draft ratio (H/D)	Fairway width/Ship Length
	Time in present rank
	Visibility
Ship type	Ship age
	Flag state
	Ship manning
Month	Ship type
	Seaworthiness
	Communication
	Time

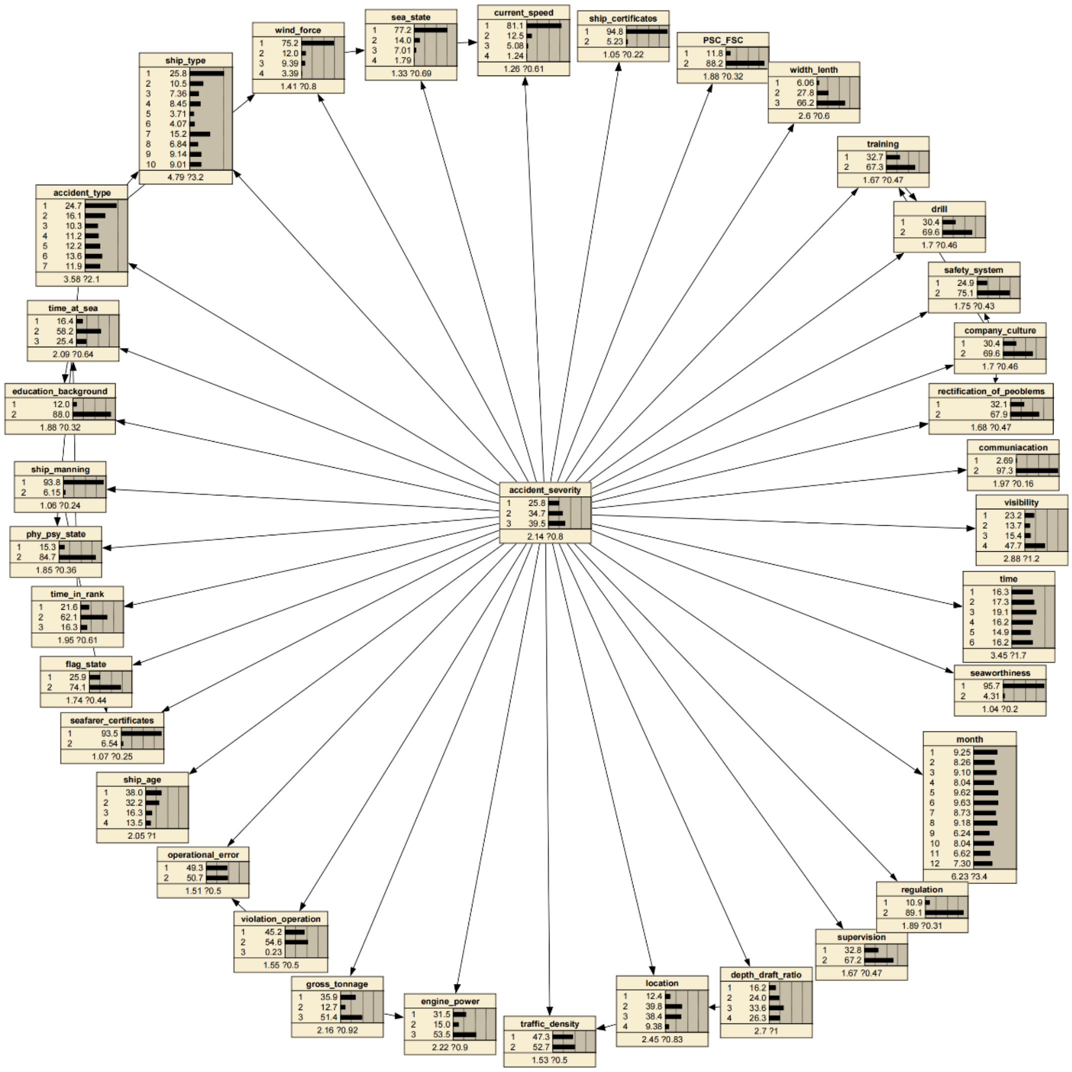

Fig. 3. Modeling results of TAN-BN.

Based on the TAN-BN model established in Fig. 3, the CPTs of all nodes can be calculated to obtain the posterior probability of each variable. Then, each CPT at this time is modified by using

Fig. 3 following the use of expert judgment. Therefore, effective information about the relationship between the severity of marine accidents and influential factors can be obtained by analyzing the relevant AIFs.

4.2 Sensitivity analysis

4.2.1 Mutual information

In this study, mutual information can be used as a measure to characterize the degree of relationship between influential factors and class variables. Therefore, according to the calculation method of mutual information value in Eq. (3) and the TAN-BN model in Fig. 3, this study analyzes and calculates the mutual information between related factors and the severity of marine accidents.

Table shows the mutual information value between "accident severity" and each AIFs in the TAN-BN model. Since the TAN-BN model established in this study takes "accident severity" as its parent node, when the mutual information value is larger, the corresponding variable has a greater impact on "accident severity", and the node "accident type" with the mutual information value of 0.25554 has the greatest impact on class variables.

Table 5 Mutual information between AIFs and "Accident Severity".

Node	Mutual Information	Percent	Variance of Beliefs
Accident type	0.25554	16.3	0.0487978
Engine power	0.10594	6.78	0.0193506
Gross tonnage	0.1012	6.47	0.0178318
Ship type	0.08282	5.3	0.0175808
Location	0.02725	1.74	0.0049555
Safety system	0.02318	1.48	0.0031612
Visibility	0.02142	1.37	0.0036286
Drill	0.02078	1.33	0.0033224
Ship age	0.02074	1.33	0.0039497
Rectification of problem	0.02034	1.3	0.0026059
Width length	0.01998	1.28	0.0032698
Company culture	0.01903	1.22	0.0021741
Training	0.01741	1.11	0.0027337
Time	0.01724	1.1	0.0028676
PSC FSC exam	0.0148	0.947	0.0025012
Sea state	0.01473	0.942	0.0033939
Time in rank	0.01381	0.883	0.0027797
Education background	0.01313	0.84	0.0024164
Month	0.01303	0.833	0.0018662
Time at sea	0.01136	0.727	0.0018887
Seafarer certificates	0.01104	0.706	0.0026789
Depth draft ratio	0.01083	0.693	0.0013852
Wind force	0.01028	0.657	0.0021378
Violation operation	0.00912	0.583	0.0011223
Ship manning	0.0084	0.537	0.0016262
Regulation	0.00668	0.427	0.0007406
Current speed	0.00598	0.382	0.0010653
Seaworthiness	0.00597	0.382	0.0008956
Traffic density	0.00566	0.362	0.0007355
Supervision	0.00509	0.325	0.0006244
Ship certificates	0.00463	0.296	0.0009759
Operational error	0.0012	0.0768	0.0002156
Physical & Psychological state	0.00082	0.0524	0.0001542
Communication	0.00071	0.0453	0.0001352
Flag state	0.00038	0.0242	0.0000536

In order to select AIFs that have a greater impact on "accident severity", the first five variables with a greater mutual information value, such as "accident type", "engine power", "gross tonnage", "ship type" and "location", are selected as important AIFs for subsequent sensitivity analysis.

4.2.2 Sensitivity analysis

After screening the important AIFs, the joint probability and TRI are further calculated to analyze the impact of related factors on the severity of the accident. Table shows the joint probability between each state of the selected AIFs and the target variable.

Table 6 Joint probability between significant AIFs and accident severity.

Accident type	S1	S2	S3
1	29.1	50.8	20.1
2	**41.9**	44.9	**13.3**
3	18.3	44.1	37.6
4	17.6	**62.6**	19.8
5	**6.22**	9.99	**83.8**
6	32.3	10.1	57.5
7	24.2	**6.41**	69.3

Engine power	S1	S2	S3
1	**12.7**	**24.4**	**62.9**
2	20	30.8	49.1
3	**35.2**	**41.8**	**23**

Ship type	S1	S2	S3
1	**35.5**	38.8	**25.7**
2	30.8	41	28.1
3	28.4	43.4	28.2
4	23.7	**48.3**	28
5	33.5	37.1	29.5
6	24.2	29.6	46.2
7	**9.32**	**19.6**	**71.1**
8	20.8	32.1	47.1
9	26.3	27.8	45.9
10	21	31.4	47.6

Gross tonnage	S1	S2	S3
1	**13**	**25.9**	**61.1**
2	19.9	35.5	44.6
3	**36.2**	**40.6**	**23.2**

Location	S1	S2	S3
1	**16.7**	**47.6**	35.7
2	**30.8**	36	33.2
3	23.6	**27.2**	**49.2**
4	25.9	42.9	**31.2**

Table shows the state of each variable that has the greatest and least impact on accident severity (see bold). For example, the most likely accident type of "Less serious casualties and marine incidents" is "stranding/grounding" (41.9%), the most likely accident type of "serious accident" is "contact" (62.6%), and the most likely accident type of "very serious accident" is "capsizing/sinking" (83.8%). In terms of "engine power" and "tonnage", ships with "less than 750KW" and "less than 500T" are more likely to have "very serious accidents" (62.9% and 61.1%), and ships with "more than or equal to 3000KW" and "more than or equal to 3000T" are more likely to have "Less serious casualties and marine incidents" (35.3% and 36.2%). "Fishing ships" are more likely to have "very serious accidents" (71.1%) and less likely to have "Less serious casualties and marine incidents" and "serious accidents" (9.32% and 19.6% respectively), while "bulk carriers" are more likely to have "Less serious casualties and marine incidents" (35.5%). "Coastal areas" are more likely to occur "very serious accidents" (49.2%), "ports" are more likely to occur " Less serious casualties and marine incidents " (30.8%), and "inland waters" are more likely to occur "serious accidents" (47.6%). The analysis of the joint probability data can show the probability of the occurrence of an accident grade and some influential factors in the accident, and explain the influence of some states of a single variable on the severity of an accident.

By calculating the average TRI values of different accident severity grades and prioritizing them, the influence of relevant variables on "accident severity" can be illustrated. The higher the TRI, the greater the influence of the corresponding AIF node on the "accident severity". Table shows the TRI values of different accident severity grades corresponding to different "accident type" states.

Table 7 TRI values of different states of "accident type" corresponding to accident severity grade.

Accident type										
1	2	3	4	5	6	7	S1	HRI	LRI	TRI
/	/	/	/	/	/	/	25.8	16.1	19.58	17.84
100%	0	0	0	0	0	0	29.1			
0	100%	0	0	0	0	0	41.9			
0	0	100%	0	0	0	0	18.3			
0	0	0	100%	0	0	0	17.6			
0	0	0	0	100%	0	0	6.22			
0	0	0	0	0	100%	0	32.3			
0	0	0	0	0	0	100%	24.2			
1	2	3	4	5	6	7	S2	HRI	LRI	TRI
/	/	/	/	/	/	/	34.7	27.9	28.29	28.095
100%	0	0	0	0	0	0	50.8			
0	100%	0	0	0	0	0	44.9			
0	0	100%	0	0	0	0	44.1			
0	0	0	100%	0	0	0	62.6			
0	0	0	0	100%	0	0	9.99			
0	0	0	0	0	100%	0	10.1			
0	0	0	0	0	0	100%	6.41			
1	2	3	4	5	6	7	S3	HRI	LRI	TRI
/	/	/	/	/	/	/	39.5	44.3	26.2	35.25
100%	0	0	0	0	0	0	20.1			
0	100%	0	0	0	0	0	13.3			
0	0	100%	0	0	0	0	37.6			
0	0	0	100%	0	0	0	19.8			
0	0	0	0	100%	0	0	83.8			
0	0	0	0	0	100%	0	57.5			
0	0	0	0	0	0	100%	69.3			

In Table , taking "Less serious casualties and marine incidents" as an example, 25.8% in the first row represents the initial probability of "general accident" in the model, and each row below represents the probability of "general accident" when different states respectively reach 100% , for example, in the second row, the probability of “state 1” of the accident type is set to 100% (other state probability is 0), the probability of "Less serious casualties and marine incidents" is 29.1%; in the third row, the probability of “state 2” of the accident type is set to 100% (other state probability is 0), the probability of "Less serious casualties and marine incidents" is 41.9%, and so on. After the calculation of all the states, it can be found that the maximum probability value of "Less serious casualties and marine incidents" is 41.9%, which corresponds to “state 2” of accident type. The minimum probability of "Less serious casualties and marine incidents" is 6.22%, which corresponds to “state 5”. Therefore, by calculating the difference between the calculated maximum and minimum probability values and the initial probability, HRI and LRI are obtained as 16.1% and 19.58%, respectively. Then, the average value of HRI and LRI is taken to obtain the TRI of "Less serious casualties and marine incidents" corresponding to different "accident type" states is 17.84%. In this way, the TRI values of important AIFs under different accident severity grades are shown in Table .

Table 8 TRI values of important AIFs under different accident severity grades.

Node	TRI			
	S1	S2	S3	Average
Accident type	17.84	28.095	35.25	27.0617
Engine power	11.25	8.7	19.95	13.3
Gross tonnage	11.6	7.35	18.95	12.6333
Ship type	13.09	14.35	22.7	16.7133
Location	7.05	10.2	9	8.75

Table shows the TRI of the important AIFs for different accident severity grades. By comparing and ranking the TRI, the decreasing ranking of the most important variables for the accident severity is shown as follows:

Accident type > Ship type > Engine power > Gross tonnage > Location

Then, the important AIFs variables under different accident severity grades are ranked according to the above method, as shown in Table :

Table 9 TRI value ranking of important AIFs.

Accident severity	Accident type	Engine power	Gross tonnage	Ship type	Location
S1	1	4	3	2	5
S2	1	4	5	2	3
S3	1	3	4	2	5

As can be seen from Table , there are both similarities and differences in the prioritization of the influence of different variables under different accident severity grades. For example, "Accident type" and "ship type" are consistently the most important AIFs among the three accident severity grades. In the comparison of "Very serious accident" with "Less serious casualties and marine incidents" and "Serious accident", "main engine power" has more influence than "tonnage" and "accident location". For "Very serious accidents", the influence ranking of the above variables is consistent with the average TRI. At the same time, this method not only illustrates the influence degree of single factor on the target node of the network model, but also shows the influence degree of multi-factor superposition on the target node.

4.2.3 Model validation

In the process of model verification, since the TAN-BN model nodes have certain correlation and each target node has different independent states, this study observes the model results by calculating the change of different states of each node to verify the reliability of the model. In the process of model verification, the selected important AIFs are taken as the target nodes and the different states of different nodes are adjusted successively. The specific process is as follows: (1) select "Accident Type" as the first verification node, increase the value of the state that has the greatest impact on "accident severity" by 10%, (2) and decrease the value of the state that has the least impact on "accident severity" by 10% in this node, this process is expressed as "~10%" in Table , (3) apply the same method to " engine power", "tonnage", "ship type" and "position" successively, and record the accumulated variation. At the same time, the same verification process is successively applied to different grades of "accident severity" until all the accident severity states are included. The specific results are shown in Table .

Table 10 Influence of the change of target node status on different accident severity grades.

Accident type	/	~10%	~10%	~10%	~10%	~10%
Engine power	/	/	~10%	~10%	~10%	~10%
Gross tonnage	/	/	/	~10%	~10%	~10%
Ship type	/	/	/	/	~10%	~10%
Location	/	/	/	/	/	~10%
S1	25.8	29.4	31.7	34	36.8	38.6
S2	34.7	41	42.7	44	47.5	49.7
S3	39.5	46.5	50.6	54.5	58.6	60.3

It can be seen from Table , the original data in the TAN-BN model in the first column is the probability of occurrence of different accident severity grades, and the accumulated data after changes in the verification process in each subsequent column. Besides, the calculation for different accident severity grades is independent, that is, each row is calculated independently. Specifically, the first line of "25.8%" is the original value of the "Less serious casualties and marine incidents", let the biggest impact of the state in "accident type" to the "Less serious casualties and marine incidents" value increased by 10%, the minimal impact of the state in "accident type" decreases by 10%, so the state of the "Less serious casualties and marine incidents" status value change to "29.4%". On this basis, the same steps are successively performed for "engine power", "tonnage", "ship type" and "position" nodes to obtain the corresponding change values. In addition, apply the same validation process to "Serious accidents" and "Very serious accidents" until all calculations are completed. It can be found from Table that the change law of the state value of the target node conforms to Axiom 1. By comparing the initial state values of different accident severity grades with the updated node state values, with the increase and decrease of the corresponding states of related AIFs, the state change of the target node conforms to Axiom 2, verifying the reliability of this model.

In addition, the receiver operating characteristic curve (ROC) is used to verify the accuracy of the model data. The abscissa of the curve is the false positive rate, and the ordinate is the true positive rate. The area under the curve (AUC) can be used to judge the reliability of the model. Generally, the value of AUC is greater than 0.5 and less than 1, and the larger the AUC is, the better the reliability of the model is (Wang and Yang, 2018).

With the severity of the accident as the target node, the state of the three severity grades is treated with binary classification. The TAN-BN models corresponding to Fig. 2 and Fig. 3 are tested and compared by Netica software, respectively. The corresponding verification results of different severity grades of accidents are shown in Table . It can be found from Table that the AUC of the TAN-BN model established in this study is all greater than 0.5 for the three grades of accident severity, and the AUC value of the TAN-BN model in Fig. 3 modified by combining expert knowledge is larger and its performance is better.

Table 11 AUC corresponding to different grades of accident severity.

State	S1	S2	S3
Fig (2)-AUC	0.7996	0.7503	0.7446
Fig (3)-AUC	0.8738	0.8997	0.9148

In addition, historical accident investigation reports, which are not included in the accident report database of this study, can also be used to validate the model. For example, this study selects the marine accident investigation report (MAIB15-2021) issued by MAIB as the object of case analysis. The incident occurred on 28/03/2020, near the factory pier on the Isle of Skye in Scotland. A chemical ship named Key Bora ran aground 400 meters from the pier for about 12 minutes before refloating. There were no injuries or contamination, minor structural damage to the ship, the severity grade of the accident belongs to the "Less serious casualties and marine incidents" established by this study. Through the analysis of the accident report, the relevant information of the accident is as follows:

1) The type of accident is "stranding/grounding", and the time of accident is "1505 28/03/ 2020";
2) The ship type is "chemical ship", the ship age is "14 years", the gross tonnage is "2627T", the crew fitness certificate is "complete and valid", since Key Bora's crew comprised of 6 officers and 6 crew who were all suitably qualified for their roles in accordance with The minimum safe manning certificate;
3) The captain involved has "> 10 years of sea experience", "> 5 years of service", and "good" theoretical knowledge level. Since the master was a 48-year-old Polish national who had worked at sea for 30 years. He had over 15 years' experience in Chemical tankers, including 8 years as master. The communication is "good", because of "effective communication", but there are mistakes in the operation process of the relevant crew. Since the bridge team relied on locally produced survey data that did not show a boulder obstruction near the pier.
4) The accident occurred in the waters near the "port", at which time the wave speed is "2kts";
5) For the shipping enterprises involved in the accident, the correction of the problem is "not timely", because the relevant departments fail to find the problems in the Electronic Chart Display and Information System (ECDIS) and correct them in time.

Although some information in the accident report is not recorded, this study sets the state parameters of relevant nodes according to the existing data, and the output result of the model shows that there is 74.6% probability of "Less serious casualties and marine incidents", which is also consistent with the actual situation of the accident, and further verifies the reliability of the model, as shown in Fig. 4:

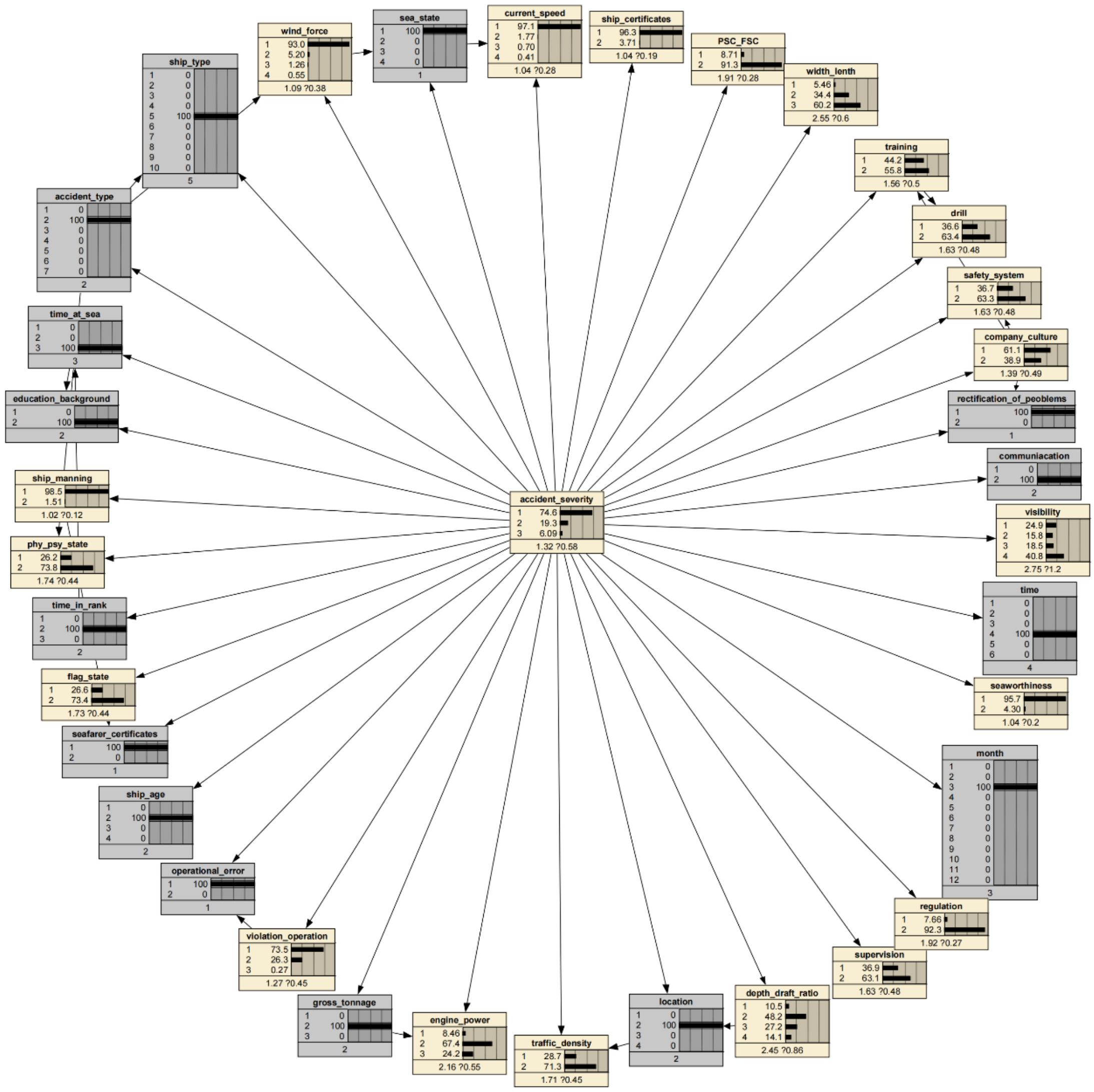

Fig. 4. Model validation based on a real case.

4.3 Implications (MPE)

In order to observe the connections between related nodes in BN and find the most likely state of occurrence in a node, TAN-BN model can provide the most likely explanation (MPE) based on the determined accident severity, which is also a special case of maximum posterior probability. Using the MPE mode of BN, the most likely AIFs in the current scenario can be observed, and the known scenario can be updated by manual input of evidence, that is, the most likely AIFs in an accident under a known severity grade can be observed. This method can provide a more comprehensive and reliable scheme for the analysis of marine accidents, predict the causes of accidents, and help prevent the occurrence of marine accidents.

In the MPE mode, each node will have at least one 100% level confidence bar, and usually several lower level confidence bars, which can be manually set to 100% level for each node to obtain the most likely other configuration information. If the other nodes are in the most likely configuration, the shorter bars represent the relative probabilities (scaled) of the other states, as shown in Fig. 5.

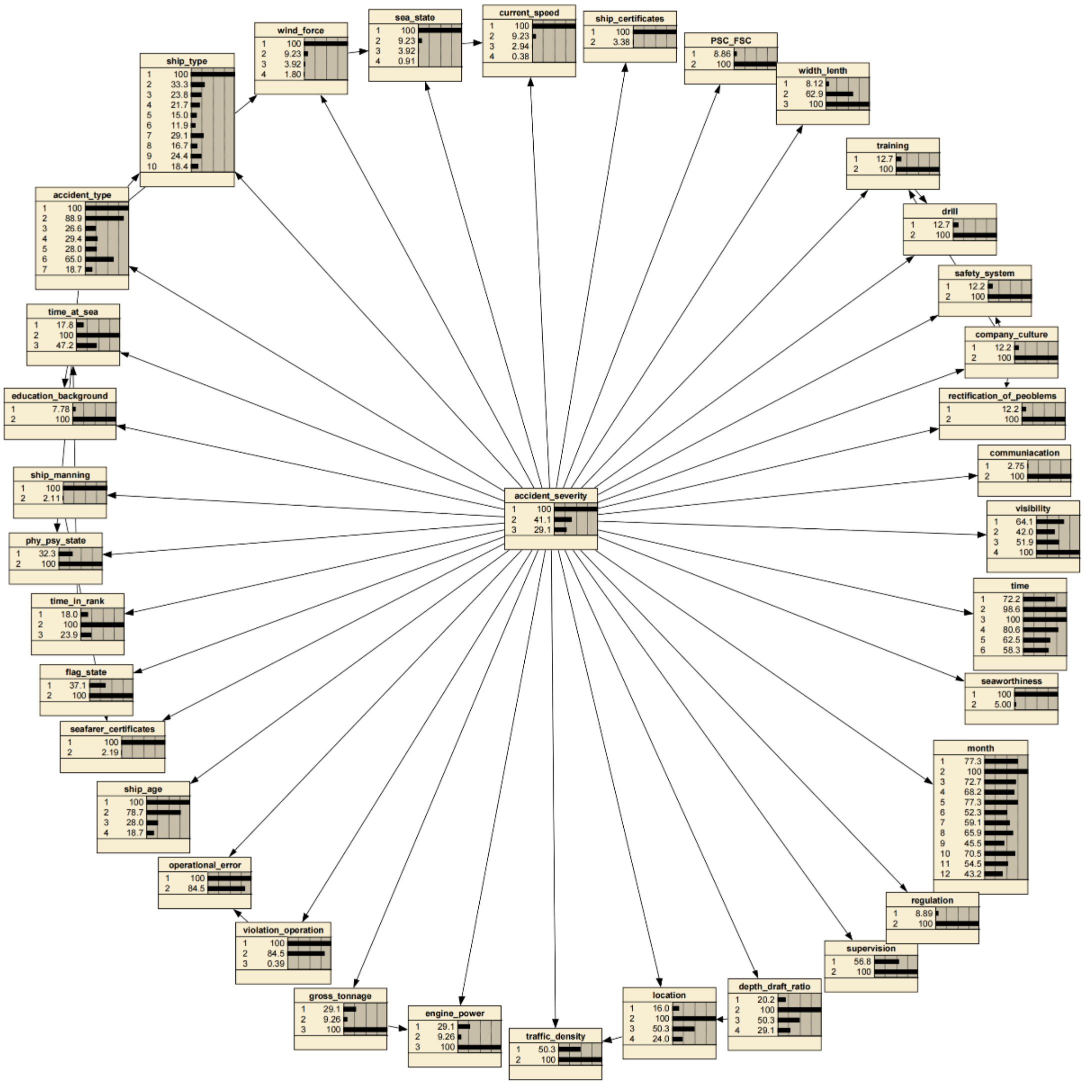

Fig. 5. MPE mode.

As can be seen from Fig. 5, "Less serious casualties and marine incidents" occur with a high frequency and have the most likely accident severity grade. The relevant important AIFs screened in the previous section show the corresponding most likely state, that is to say, there is a high probability that a "Less serious casualties and marine incidents" caused by a "collision" will occur to a "bulk carrier" under the following circumstances:

1) Gross tonnage is "greater than or equal to 3000GT", engine power is "greater than or equal to 3000KW";

2) the ship is located in the "port" and the traffic density is "high"; and

3) "errors" and "violations" in crew operation.

Through the above configuration, it can be found that the result after the collision accident depends on the ship's own condition and external environment to a certain extent, and the ship's own condition mainly includes ship factors and human factors. From the analysis of ship factors, it can be seen that, generally speaking, large ships have longer turning basin and stop time than small ships. From the perspective of navigation environment, it is more difficult for large ships to operate in waters with high navigable density, such as port areas or waterways, and the possibility of collisions is higher. From the analysis of human factors, it can be found that the crew's operation errors and violations may lead to the collision. Such errors and violations include the insufficient risk assessment, the unclear command, the late steering or even the reverse steering and other navigational behaviors.

The above scenario configuration also reflects the causal relationship between the relevant factors and the severity of accident, so as to avoid the evolution of "Less serious casualties and marine incidents" into "serious accident" and "very serious accident" to a certain extent. For example, in terms of ship scale, the stability of large ships is higher than that of small ships. Therefore, in case of collision, large ships are relatively safer, and it is more likely that the accident severity grade is lower. For the accident type, collision is different from sinking/capsizing and other types of accidents. The consequences of collision depend on the degree of collision, For example, the collision of commercial fishing ships often leads to "very serious accident" for fishing ships, while "serious accident" or " Less serious casualties and marine incidents " may occur for merchant ships. In addition to operation errors, better navigation environment and management can also prevent "Less serious casualties and marine incidents" from evolving into "serious accidents" and "very serious accidents" to a certain extent.

Similarly, Fig. 6 shows the interpretation when "accident severity" is selected as "very serious accident" in the MPE mode:

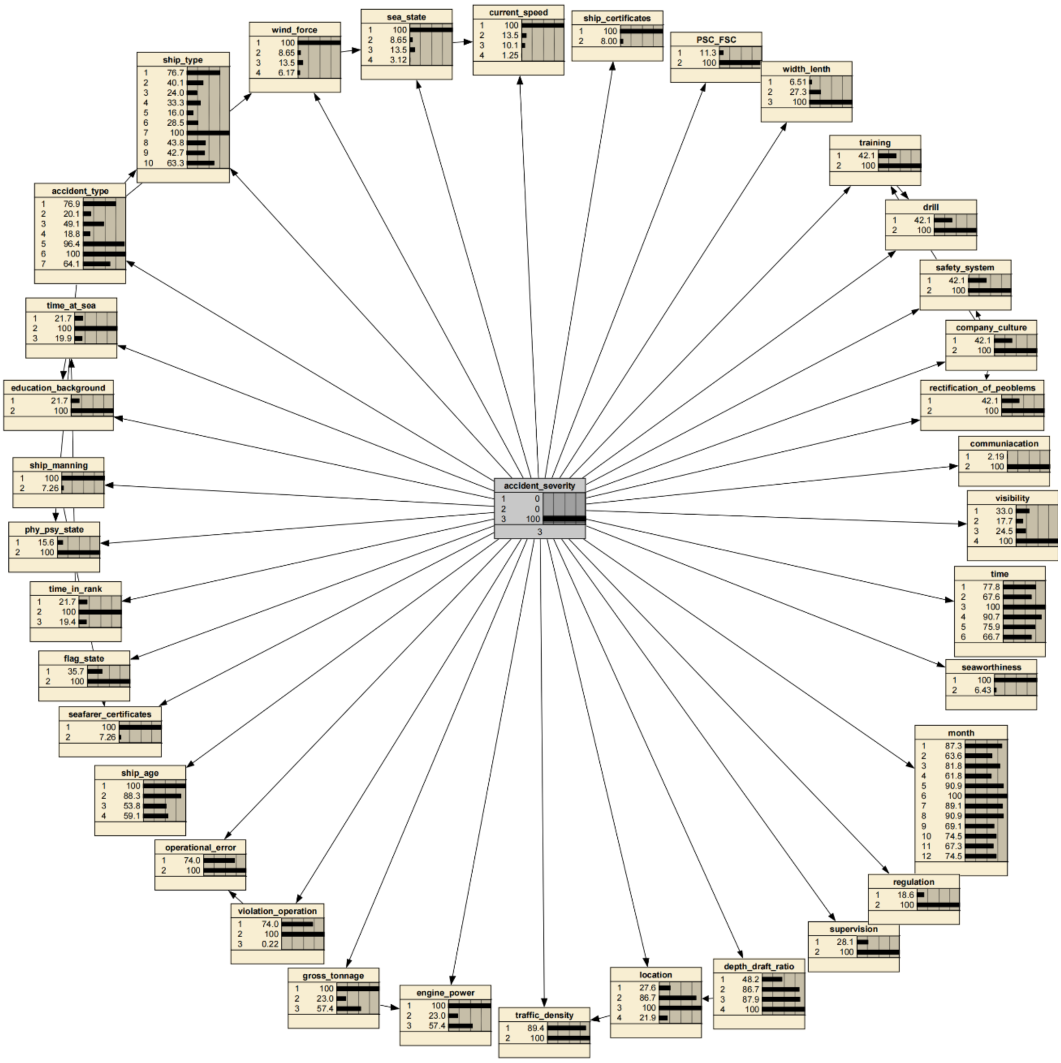

Fig. 6. MPE scenario for a "very serious accident".

As can be seen from Fig. 6, after setting "very serious accident" as the most likely accident severity grade, other AIFs also change accordingly compared with Fig. 5:

1) The ship type is "fishing ship", the gross tonnage is "< 500GT", and the engine power is "< 750KW".
2) The type of accident is "hull/machinery damage".
3) The ship is located "coastal area" and the traffic density is "high".

According to the configuration in Fig. 6 and the analysis above, the consequences and severity of the accident are closely related to the important AIFs selected above. During the actual voyage of a ship, especially a fishing ship operating offshore, the ship size is usually smaller, and due to cost constraints, the ship is in poor condition and the possibility of hull/machinery damage is higher. Based on the above conditions, in the event of an accident, if it is affected by human error or the adverse environment, it is more likely to cause a more serious accident.

In addition, when establishing the database of accident risk factors, besides human factors, ship factors and environmental factors, management factors are also taken as the first-level indexes affecting the severity of accidents. When mutual information is used to screen important AIFs, although the mutual information value corresponding to the three-level indexes of related management factors is not large, it can be found that there is an important causal relationship between management factors and accident severity under the MPE mode. In fact, the management factors include the maritime authority, the shipping company and the ship. The AIFs contained therein are further subdivided into regulation, supervision, safety management system, rectification of problems, and company safety culture, training, drill, etc. Taking the safety management system as an example, set the safety management system node state to "defective" in the MPE mode of the BN model. The configuration where other factors are most likely to appear is shown in Fig. 7:

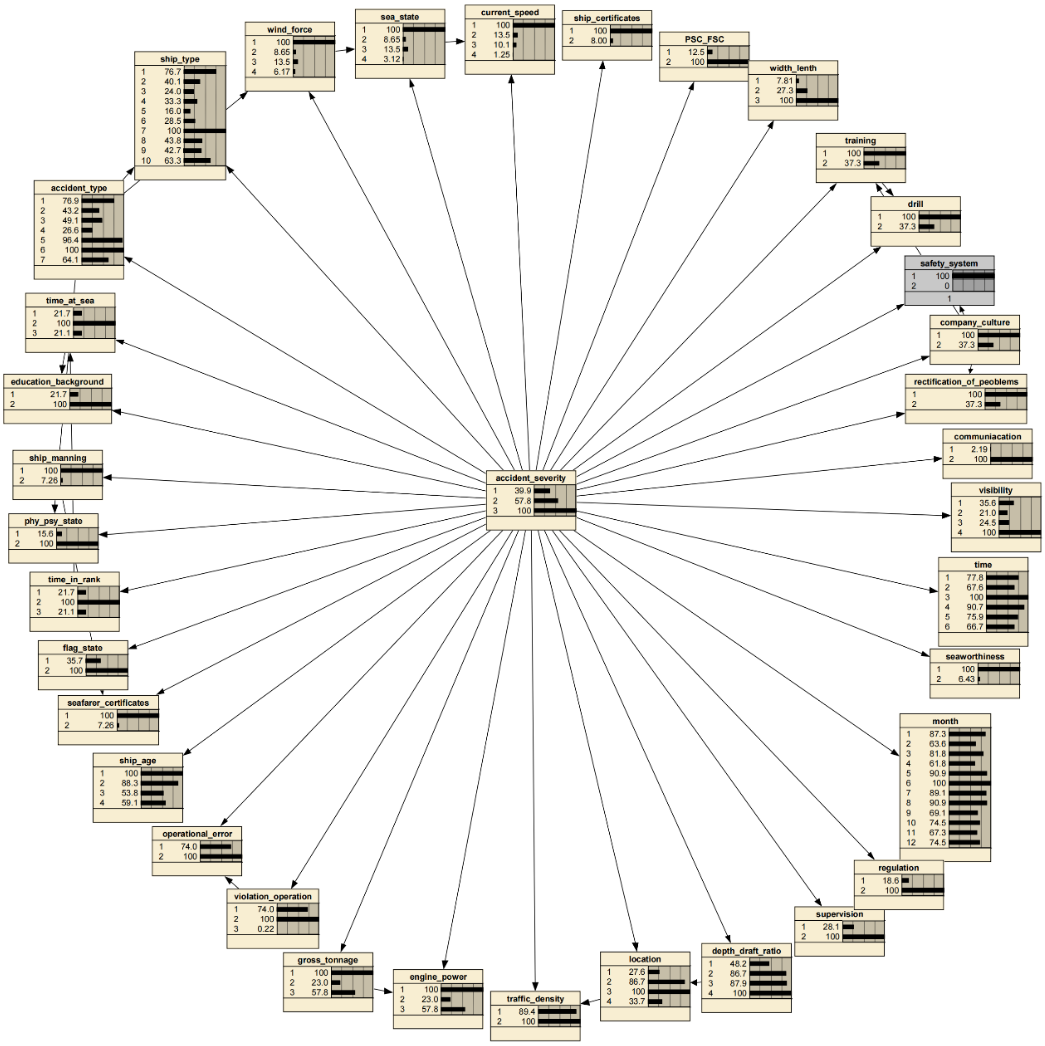

Fig. 7. MPE scenario when the "safety management system" has problems.

Comparing Fig. 7 with Fig. 5, when the safety management system node state is set to "defective," the scenario is configured as follows:

1) The ship type is "fishing boat", the gross tonnage is "< 500GT", and the main engine power is "< 750KW".
2) The type of accident is "hull/machinery damage", and the severity of accident is "very serious accident".
3) The ship is located "coastal area" and the traffic density is "high".

4) The rectification of problems is "poor", the company safety culture is "poor", the training is "not going according to plan", and the drill is "not going according to plan".

By comparing the above configuration with Fig. 5 and Fig. 6, it can be found that management factors play a very important role in the occurrence of accidents. When the probability of a variable in the management factor becomes higher, the probability of related associated variables will increase. For example, comparing the situation in Fig. 6, the probability of other management factors will also increase after the node state of "safety management system" is set to "defective" in Fig. 7. This also shows that the management factors are composed of complex multivariable combinations, and the change of a single state will cause changes of a series of factors. In contrast to the situation in Fig. 5, the state of the target node for the accident severity and other non-management factors changes when the "safety management system" node state is set to "defective" in Fig. 7, which also validates the importance of the management factors.

5. Conclusions

Based on 1,294 marine accident investigation reports from 2000 to 2019, a data-driven Bayesian Network model combining with the TAN Bayes algorithm was established to study the impact of relevant risk influential factors on the severity of accidents. In the process of identifying the influential factors of accidents, in addition to the traditional ship factors, human factors and environmental factors, this study focuses on adding management factors, which can help maritime authorities and shipping companies to improve the working mechanism and enhance the supervision and management of ships and crew to a certain extent. After the establishment of the model, through the calculation of mutual information, the first five important AIFs were screened out, namely "accident type", "ship type", "engine power", "gross tonnage" and "location", and further analysis and discussion of these important AIFs were conducted. The results show that:

1) The three accident types "capsizing/sinking", "hull/machinery damage" and "collision" are the AIFs most likely to cause “very serious casualties”. The severity of the accident is also closely related to the size of the ship. Generally speaking, small ships (such as fishing ships), passenger ships and chemical ships with special passenger and cargo properties are more likely to have "very serious casualties", because such ships are more likely to cause environmental pollution or casualties after the accident. In addition, "coastal areas" are more prone to "very serious casualties" than "ports", "inland waterways" and "open seas", because "coastal areas" have more dense traffic than "open seas", and ships generally sailing more slowly in "ports" and "inland waterways".

2) The influence of different variables on the priority of different accident severity grades is different. For example, in the comparison of "Very serious accident" with "Less serious casualties and marine incidents" and "Serious casualties", the influence of “engine power” is larger than "gross tonnage" and "location of accident". For "very serious casualties", the ranking of their impact by the relevant variables is consistent with the average TRI.

3) There is also a strong causal relationship between management factors and accident severity. The change of the probability of a single variable in the management factor will cause the corresponding change of the probability of the target variable. At the same time, there is a certain correlation between the variables in the management factors. For example, the failure of the safety management system will increase the probability of the deterioration of the safety culture of the shipping company, and it will also lead to the higher possibility of the ship not following the planned

drill and training.

In general, the TAN-BN model established in this study explains the related factors affecting the severity of marine accidents in different perspectives, for the analysis of marine accidents and the safe management of ships. However, there are still some limitations in this study. For example, a BN model is used on the assumption that the sample and variables are independent with each other, and the relationship between nodes also needs to be determined in the process of machine learning, which often needs further discussion in the actual application. In this study, the relationship between nodes is improved on the basis of the data driven and expert knowledge. However, if there are irrelevant connection between nodes, the results may be biased. Therefore, in further studies, researchers can use a BN model combined with other methods to enhance the reliability of the results. In addition, the collection and assessment of subjective data associated with human factors and management factors should be strengthened, which is also helpful to improve the quantitative analysis of marine accidents.

References

Acharya, T.D., Yoo, K.W., Lee, D.H., 2017. GIS-based Spatio-temporal Analysis of Marine Accidents Database in the Coastal Zone of Korea. *Journal of Coastal Research* 79, 114-118. https://doi.org/10.2112/SI79-024.1

Afenyo, M., Khan, F., Veitch, B., Yang, M., 2017. Arctic shipping accident scenario analysis using Bayesian Network approach. *Ocean Engineering* 133, 224-230. https://doi.org/10.1016/j.oceaneng.2017.02.002

AGCS, 2022. Safety & Shipping Review 2022. Allianz Global Corporate & Specialty, Munich.

Alyami, H., Yang, Z., Riahi, R., Bonsall, S., Wang, J., 2019. Advanced uncertainty modelling for container port risk analysis. *Accident Analysis & Prevention* 123, 411-421. https://doi.org/10.1016/j.aap.2016.08.007

Baksh, A.-A., Abbassi, R., Garaniya, V., Khan, F., 2018. Marine transportation risk assessment using Bayesian Network: Application to Arctic waters. *Ocean Engineering* 159, 422-436. https://doi.org/10.1016/j.oceaneng.2018.04.024

Bye, R.J., Aalberg, A.L., 2018. Maritime navigation accidents and risk indicators: An exploratory statistical analysis using AIS data and accident reports. *Reliability Engineering & System Safety* 176, 174-186. https://doi.org/10.1016/j.ress.2018.03.033

Cakir, E., Fışkın, R., Sevgili, C., 2021a. Investigation of tugboat accidents severity: An application of association rule mining algorithms. *Reliability Engineering & System Safety* 209, 107470. https://doi.org/10.1016/j.ress.2021.107470

Cakir, E., Sevgili, C., Fiskin, R., 2021b. An analysis of severity of oil spill caused by vessel accidents. *Transportation Research Part D: Transport and Environment* 90, 102662. https://doi.org/10.1016/j.trd.2020.102662

Ceylan, B.O., Akyuz, E., Arslan, O., 2021. Systems-Theoretic Accident Model and Processes (STAMP) approach to analyse socio-technical systems of ship allision in narrow waters. *Ocean Engineering* 239, 109804. https://doi.org/10.1016/j.oceaneng.2021.109804

Chauvin, C., Lardjane, S., Morel, G., Clostermann, J.-P., Langard, B., 2013. Human and organisational factors in maritime accidents: Analysis of collisions at sea using the HFACS. *Accident Analysis &*

Prevention 59, 26-37. https://doi.org/10.1016/j.aap.2013.05.006
Chen, J., Bian, W., Wan, Z., Yang, Z., Zheng, H., Wang, P., 2019. Identifying factors influencing total-loss marine accidents in the world: Analysis and evaluation based on ship types and sea regions. *Ocean Engineering* 191, 106495. https://doi.org/10.1016/j.oceaneng.2019.106495
Cho, D.-O., 2007. The effects of the M/V Sea Prince accident on maritime safety management in Korea. *Marine Policy* 31 (6), 730-735. https://doi.org/10.1016/j.marpol.2007.01.005
Coraddu, A., Oneto, L., Navas de Maya, B., Kurt, R., 2020. Determining the most influential human factors in maritime accidents: A data-driven approach. *Ocean Engineering* 211, 107588. https://doi.org/10.1016/j.oceaneng.2020.107588
Deng, J., Liu, S., Xie, C., Liu, K., 2021. Risk Coupling Characteristics of Maritime Accidents in Chinese Inland and Coastal Waters Based on N-K Model. *Journal of Marine Science and Engineering* 10 (1), 4. https://doi.org/10.3390/jmse10010004
Dinis, D., Teixeira, A.P., Guedes Soares, C., 2020. Probabilistic approach for characterising the static risk of ships using Bayesian networks. *Reliability Engineering & System Safety* 203, 107073. https://doi.org/10.1016/j.ress.2020.107073
EMSA, 2021. Annual Overview of Marine Casualties and Incidents 2021. European Maritime Safety Agency, Lisbon.
Fan, S., Blanco-Davis, E., Yang, Z., Zhang, J., Yan, X., 2020a. Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. *Reliability Engineering & System Safety* 203, 107070. https://doi.org/10.1016/j.ress.2020.107070
Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., Yan, X., 2020b. Maritime accident prevention strategy formulation from a human factor perspective using Bayesian Networks and TOPSIS. *Ocean Engineering* 210, 107544. https://doi.org/10.1016/j.oceaneng.2020.107544
Friedman, N., Geiger, D., Goldszmidt, M., 1997. Bayesian Network Classifiers. *Machine Learning* 29, 131–163. https://doi.org/10.1023/A:1007465528199
Galieriková, A., 2019. The human factor and maritime safety. *Transportation Research Procedia* 40, 1319-1326. https://doi.org/10.1016/j.trpro.2019.07.183
Guo, Y., Jin, Y., Hu, S., Yang, Z., Xi, Y., Han, B., 2023. Risk evolution analysis of ship pilotage operation by an integrated model of FRAM and DBN. *Reliability Engineering & System Safety* 229, 108850. https://doi.org/10.1016/j.ress.2022.108850
Hänninen, M., 2014. Bayesian networks for maritime traffic accident prevention: Benefits and challenges. *Accident Analysis & Prevention* 73, 305-312. https://doi.org/10.1016/j.aap.2014.09.017
Hänninen, M., Kujala, P., 2014. Bayesian network modeling of Port State Control inspection findings and ship accident involvement. *Expert Systems with Applications* 41 (4, Part 2), 1632-1646. https://doi.org/10.1016/j.eswa.2013.08.060
Hänninen, M., Valdez Banda, O.A., Kujala, P., 2014. Bayesian network model of maritime safety management. *Expert Systems with Applications* 41 (17), 7837-7846. https://doi.org/10.1016/j.eswa.2014.06.029
IMO, 2000. Reports on marine casualties and incidents (MSC/Circ.953).
Jiang, M., Lu, J., Yang, Z., Li, J., 2020. Risk analysis of maritime accidents along the main route of the Maritime Silk Road: a Bayesian network approach. *Maritime Policy & Management* 47 (6), 815-832. https://doi.org/10.1080/03088839.2020.1730010

Jin, D., 2014. The determinants of fishing vessel accident severity. *Accident Analysis & Prevention* 66, 1-7. https://doi.org/10.1016/j.aap.2014.01.001

Jones, B., Jenkinson, I., Yang, Z., Wang, J., 2010. The use of Bayesian network modelling for maintenance planning in a manufacturing industry. *Reliability Engineering & System Safety* 95 (3), 267-277. https://doi.org/10.1016/j.ress.2009.10.007

Kaptan, M., Sarıalioğlu, S., Uğurlu, Ö., Wang, J., 2021. The evolution of the HFACS method used in analysis of marine accidents: A review. *International Journal of Industrial Ergonomics* 86, 103225. https://doi.org/10.1016/j.ergon.2021.103225

Li, X., Tang, W., 2019. Structural risk analysis model of damaged membrane LNG carriers after grounding based on Bayesian belief networks. *Ocean Engineering* 171, 332-344. https://doi.org/10.1016/j.oceaneng.2018.10.047

Li, Z., Hu, S., Gao, G., Xi, Y., Fu, S., Yao, C., 2021. Risk Reasoning from Factor Correlation of Maritime Traffic under Arctic Sea Ice Status Association with a Bayesian Belief Network. *Sustainability* 13 (1), 147. https://doi.org/10.3390/su13010147

Liang, X., Fan, S., Lucy, J., Yang, Z., 2022. Risk analysis of cargo theft from freight supply chains using a data-driven Bayesian network. *Reliability Engineering & System Safety*, 108702. https://doi.org/10.1016/j.ress.2022.108702

Liu, K., Yu, Q., Yuan, Z., Yang, Z., Shu, Y., 2021. A systematic analysis for maritime accidents causation in Chinese coastal waters using machine learning approaches. *Ocean & Coastal Management* 213, 105859. https://doi.org/10.1016/j.ocecoaman.2021.105859

MoT, 2014. Regulation of water transportation accident statistics. Ministry of Transport of China, Beijing.

MoT, 2022. Statistical Bulletin on Transport Industry Development. Ministry of Transport of China, Beijing.

National, A., 2005. The Merchant Shipping (Accident Reporting and Investigation) Regulations, No. 881, UK.

Navas de Maya, B., Kurt, R.E., 2020. Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs): A case study on bulk carrier's accident contributors. *Ocean Engineering* 208, 107197. https://doi.org/10.1016/j.oceaneng.2020.107197

Puisa, R., Lin, L., Bolbot, V., Vassalos, D., 2018. Unravelling causal factors of maritime incidents and accidents. *Safety Science* 110, 124-141. https://doi.org/10.1016/j.ssci.2018.08.001

Rahman, S., 2017. An Analysis of Passenger Vessel Accidents in Bangladesh. *Procedia Engineering* 194, 284-290. https://doi.org/10.1016/j.proeng.2017.08.147

Rawson, A., Brito, M., 2022. A survey of the opportunities and challenges of supervised machine learning in maritime risk analysis. *Transport Reviews*, 1-23. https://doi.org/10.1080/01441647.2022.2036864

Talley, W.K., Jin, D., Kite-Powell, H., 2008. Determinants of the severity of cruise vessel accidents. *Transportation Research Part D: Transport and Environment* 13 (2), 86-94. https://doi.org/10.1016/j.trd.2007.12.001

Tang, L., Tang, Y., Zhang, K., Du, L., Wang, M., 2019. Prediction of Grades of Ship Collision Accidents Based on Random Forests and Bayesian Networks, 2019 5th International Conference on Transportation Information and Safety (ICTIS), pp. 1377-1381.

Wang, H., Liu, Z., Wang, X., Graham, T., Wang, J., 2021. An analysis of factors affecting the severity of marine accidents. *Reliability Engineering & System Safety* 210, 107513.

https://doi.org/10.1016/j.ress.2021.107513
Wang, H., Liu, Z., Wang, X., Huang, D., Cao, L., Wang, J., 2022. Analysis of the injury-severity outcomes of maritime accidents using a zero-inflated ordered probit model. *Ocean Engineering* 258, 111796. https://doi.org/10.1016/j.oceaneng.2022.111796
Wang, L., Yang, Z., 2018. Bayesian network modelling and analysis of accident severity in waterborne transportation: A case study in China. *Reliability Engineering & System Safety* 180, 277-289. https://doi.org/10.1016/j.ress.2018.07.021
Weng, J., Yang, D., 2015. Investigation of shipping accident injury severity and mortality. *Accident Analysis & Prevention* 76, 92-101. https://doi.org/10.1016/j.aap.2015.01.002
Wu, B., Tang, Y., Yan, X., Guedes Soares, C., 2021. Bayesian Network modelling for safety management of electric vehicles transported in RoPax ships. *Reliability Engineering & System Safety* 209, 107466. https://doi.org/10.1016/j.ress.2021.107466
Xing, Y., Chen, S., Zhu, S., Zhang, Y., Lu, J., 2020. Exploring Risk Factors Contributing to the Severity of Hazardous Material Transportation Accidents in China. *International Journal of Environmental Research and Public Health* 17 (4), 1344. https://doi.org/10.3390/ijerph17041344
Xue, J., Papadimitriou, E., Reniers, G., Wu, C., Jiang, D., van Gelder, P.H.A.J.M., 2021. A comprehensive statistical investigation framework for characteristics and causes analysis of ship accidents: A case study in the fluctuating backwater area of Three Gorges Reservoir region. *Ocean Engineering* 229, 108981. https://doi.org/10.1016/j.oceaneng.2021.108981
Yang, Z., Yang, Z., Yin, J., 2018. Realising advanced risk-based port state control inspection using data-driven Bayesian networks. *Transportation Research Part A: Policy and Practice* 110, 38-56. https://doi.org/10.1016/j.tra.2018.01.033
Yip, T.L., Jin, D., Talley, W.K., 2015. Determinants of injuries in passenger vessel accidents. *Accident Analysis & Prevention* 82, 112-117. https://doi.org/10.1016/j.aap.2015.05.025
Zaccone, R, Martelli, M.A. 2020. Collision avoidance algorithm for ship guidance applications. Journal Of Marine Engineering and Technology 19, 62-75.
Zhang, D., Yan, X.P., Yang, Z.L., Wall, A., Wang, J., 2013. Incorporation of formal safety assessment and Bayesian network in navigational risk estimation of the Yangtze River. *Reliability Engineering & System Safety* 118, 93-105. https://doi.org/10.1016/j.ress.2013.04.006
Zhang, G., Thai, V.V., 2016. Expert elicitation and Bayesian Network modeling for shipping accidents: A literature review. *Safety Science* 87, 53-62. https://doi.org/10.1016/j.ssci.2016.03.019
Zhang, M., Zhang, D., Yao, H., Zhang, K., 2020. A probabilistic model of human error assessment for autonomous cargo ships focusing on human–autonomy collaboration. *Safety Science* 130, 104838. https://doi.org/10.1016/j.ssci.2020.104838
Zhao, X., Yuan, H., Yu, Q., 2021. Autonomous Vessels in the Yangtze River: A Study on the Maritime Accidents Using Data-Driven Bayesian Networks. *Sustainability* 13 (17), 9985. https://doi.org/10.3390/su13179985