A mutual information-based Bayesian network model for consequence estimation of navigational accidents in the Yangtze River

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Abstract: Navigational accidents (collisions and groundings) account for approximately 85% of maritime accidents, and consequence estimation for such accidents is essential for both emergency resource allocation when such accidents occur and risk management in the framework of a formal safety assessment. As the traditional Bayesian network requires expert judgement to develop the graphical structure, this paper proposes a mutual information-based Bayesian network method to reduce subjective bias. The core of the proposed Bayesian network method is to calculate mutual information to obtain the quantitative part among multiple influencing factors by using 797 historical navigational accident records from 2006-2013. Consequently, it is expected that the model will provide a practical and reasonable method for consequence estimation of navigational accidents.

Key words: navigational accidents; consequence estimation; Bayesian network; mutual information

1 Introduction

Collision and grounding accidents account for approximately 85% of maritime accidents, and these two types of accidents are defined as navigational accidents (Wróbel et al., 2017; Erol et al., 2018). Consequence estimation for navigational accidents is essential in the risk domain (Baniela and Ríos 2011). As defined by Kaplan (1997), risk is a combination of likelihood and consequence in different scenarios. This opinion is widely accepted (Mazaheri et al., 2014) and adopted in the well-known formal safety assessment framework (Wang, 2001); risk mitigation should be carried out by decreasing the likelihood or reducing the consequence in the risk control option step (Zhang et al., 2016; Wang et al., 2019). Moreover, from the viewpoint of emergency management (Jasionowski, 2011; Xiong et al., 2015), if the consequences can be predicted, the response actions will be easy to perform in restricted conditions (Wu et al., 2018).

The Bayesian network (BN) is widely used for quantitative risk assessment (Zhang et al., 2016), especially for consequence estimation (Zhang et al., 2013; Zhang et al., 2016) in maritime transportation because of the intuitive graphical structure and quantitative presentation of the relationships among influencing factors. In practice, when introducing BNs, the historical data should be collected to develop the quantitative component (Zhang et al., 2016).

Another significant part of BNs is the qualitative component, and in practice, it always relies on expert judgements (Wu et al., 2017b; Zhang et al., 2012). However, this may cause some subjective influence on the results. To reduce the abovementioned subjective influence, mutual information, which was first proposed by Shannon and Weaver (1949), is introduced in this paper. The principle of mutual information (Li et al., 2009) is that it can be used as an indicator of the mutual dependence of two factors (e.g., gross tonnage and time of day). A BN based on mutual information analyses the mutual dependence or independence among pairs of factors (Nicholson and Jitnah 1998). A BN will then be constructed with the minimum biases.

This method has been applied for the rational implementation of port state control inspection recently (Yang et al., 2018).

Note that when introducing the mutual information-based BN (Yang et al., 2018), both the graphical structure and conditional probability tables (CPTs) are derived from the dataset, this is very useful when there are adequate data for such modelling. However, in practice, the data are often inadequate for specific reasons, which makes it difficult to develop a BN only from the accident data. One reason is that some data lacks records in the dataset. When estimating the consequences of navigational accidents in this paper, the economic loss data are missing, but this is a critical factor for consequence estimation according to the regulations of the Ministry of Transportation (MoT). Another reason is that when developing the graphical structure of a BN, the intermediate factors are often introduced to intuitively describe the accident development; however, this cannot be directly collected from the accident data. Hence, the motivation of this paper is to develop a new mutual information-based BN, which only uses the mutual information to derive the relevance of the influencing factors and reduce the subjective bias, as proposed in this paper. It should be mentioned that in this paper, the subjective bias is to be reduced rather eliminated, and the comparison among three types of BNs will be discussed in detail in the discussion section.

For similar reasons, another alternative method (Akhtar and Utne, 2014; Trucco et al., 2008), which derives the inter-node relationships by using accident investigation reports, is also not adopted. This is because it is impossible to obtain the accident investigation reports of these navigational accidents in the Yangtze River, and the data set used in this paper is collected from the vessel traffic service centre, which has few descriptions of the accident development process but contains detailed data environmental factors, ship particulars and emergency resources used. Therefore, as the data set is inadequate to determine the inter-node relations by using this method, the mutual information-based BN, reduces the subjective judgements in modelling a BN, should be an alternative solution for this problem.

The remainder of this paper is organized as follows. The mutual information-based BN is introduced in Section 2, where the influencing factors are identified from the historical data and previous studies. Mutual information is calculated to define the independence of the influencing factors, and the historical data are used to establish the CPTs. Section 3 applies the proposed method for consequence estimation for the Yangtze River. Conclusions are drawn in Section 4.

2 Consequence estimation model using mutual information-based BN

2.1 Proposed mutual information-based BN model

Traditionally, there are three steps in the basic BN modelling process. The first step is to identify the influencing factors from the historical data and/or from experts. In the second step, the graphical structure (the qualitative part) is developed by using expert inputs. In the third step, the quantitative relationship is established by introducing the CPTs.

The proposed consequence estimation model for navigational accidents is shown in Figure 1. The modelling process can be summarized in the following 3 steps.

The first step is to identify the influencing factors from the historical data and previous studies. Moreover, the associated states and probabilities are also defined in this step. In this step, two rules are defined to exclude some irrelevant factors in the accident database. Afterwards, three different types of methods are utilized to define the states of the factors together with the probabilities of the associated states.

The second step is to construct the graphical structure by using the mutual information. After obtaining the marginal probability for two influencing factors (any one with another), the mutual information can be obtained. The calculation result of the mutual information can be used to determine the dependence of the two factors by defining a threshold for the mutual information. However, it should be mentioned that the mutual information can only be used to determine the dependence or independence between two factors; it cannot be used to determine which one is the parent or child node. In practice, work experience or expert judgement should be used.

Third, the quantitative component of the BN can be established by using the CPTs because the majority of factors are derived from the accident database, which can be easily obtained. However, in this paper, as the economic loss is not recorded in the database, this intermediate factor should be introduced to facilitate the modelling process.

The main difference between the proposed mutual information-based method and the basic BN is the establishment of a qualitative part. In the basic BN, the qualitative part is established by using experts. However, the proposed method uses the existing information to determine the dependence among all of the variables. Although work experience or expert judgements are used to define the parent and child nodes after obtaining the dependence relationship of the influencing factors, this is much easier and can largely reduce the subjective influence on the qualitative relationship rather than solely relying on expert opinions. The chi-square independence test can also be used to determine the dependence between two variables in the second step. The advantage of mutual information is that it is useful for small datasets, while the chi-square independence test requires the asymptotic limit of infinite data (Pethel and Hahs 2014). This paper will not further discuss the advantages and disadvantages but rather chooses the mutual information-based method because they are all widely used and have similar results in practice.

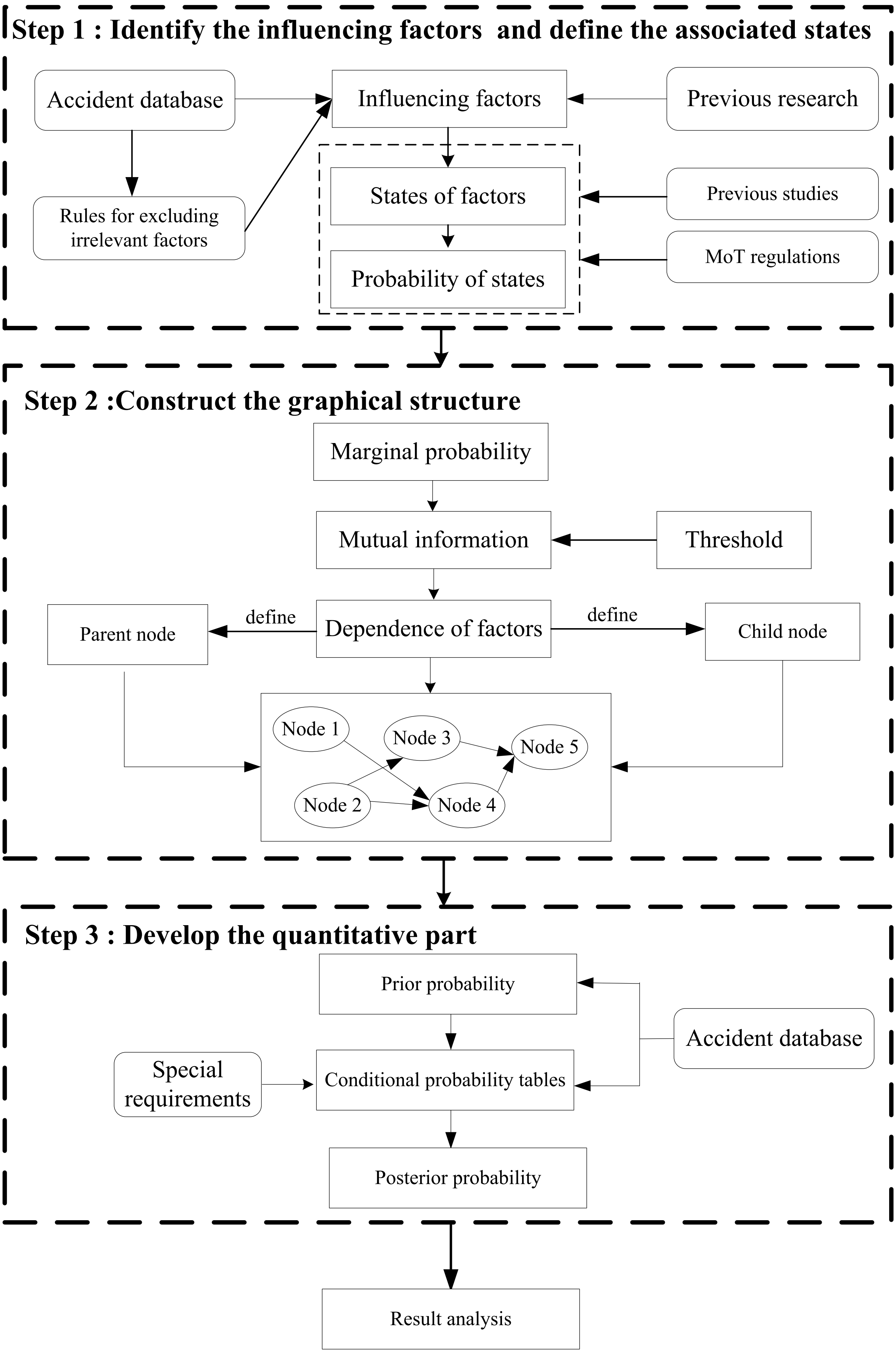

Fig. 1 Proposed mutual information-based BN for consequence estimation

2.2 Identify the influencing factors for the consequence estimation of navigational accidents

Because there are more than 20 factors recorded in this database and to simplify the modelling process, the influencing factors should be excluded according to the following two rules. Note that the excluded factors will not be considered in the BN model, and only factors that are strongly related are excluded.

On the one hand, if one factor can strongly relate with another factor, only one of the factors should be selected in this modelling process. Taking the “ship length” and “gross tonnage” as examples, these two factors have a strong relationship with an $R^2 = 0.956$ when polynomial curve fitting is applied, and only the factor “gross tonnage” is selected. On the other hand, if one factor has a weak relationship with the other factors, this factor should be excluded in this modelling process. This can also be achieved by using mutual information. To illustrate this phenomenon, the factor “ship owner” will be used in this paper, and the result is shown in Subsection 3.1.

After using these two rules, the influencing factors can be identified from the following previous studies. The influencing factors of wind, visibility, time of day and arrival time of the tug boat have an important impact on maritime safety control in the Yangtze River (Wu et al., 2018; Liu et al., 2016). The influencing factors of the ship gross tonnage and the position of the accidents is used for decision support of grounded ships (Wu et al., 2017b). Emergency resources is used and the number of people in distress is used for the evaluation of the effectiveness of search and rescue operations (Zhang et al., 2014). It should be mentioned that the emergency resources used indicates how many types of emergency resources have been used in the emergency response. In practice, helicopters, costal patrol vessels, civil ships and tug boats are treated as one type of emergency resource. The ship type was found to be related to oil spillages in a previous study (Yip et al., 2011). Pollution, economic loss, loss of ship and number of fatalities are directly related to the consequences of the MoT regulations in China, which makes them easy to obtain.

2.3 Determine the states of the influencing factors

The node states should be carefully handled when using a BN. The reasons why the node states are defined is shown in Table 1. To define feasible and reasonable states for all nodes, three types of methods are used in this paper.

First, as the states of some nodes are described using linguistic terms in the database and it is very easy to define them by using the existing linguistic terms. For example, in the database, pollution is described as yes or no. Similarly, the nodes for time of day and visibility, loss of ship, and hull damage after collision are defined in this way.

Second, some states, such as the wind condition, are defined according to work experience and previous studies. In the study by Balmat et al. (2011), a wind condition of less than 3 (the Beaufort scale) has little impact on maritime safety, while according to the regulations of the Maritime Safety Administration (MSA), ships are prohibited to navigate in the fairway when the wind condition is more than 6. Therefore, the states of the wind can be defined as less than 3, from 3 to 6, and more than 6. The emergency resources used, ship type, arrival time of the tug boat, position of the accident, run aground, tug assistance, flooding and condition after an intervention are all defined in this way.

Table 1 Reasons for defining the node states

Node name	Node states	Reasons
time of day	daytime/night-time	The emergency response actions are restricted at night
Wind condition (Beaufort Scale)	Less than 3/from 3 to 6/more than 6	Less than 3 has little impact on maritime safety, and the ships are prohibited from navigating when wind is more than 6
visibility	good/bad	The bad visibility may have a large influence on collision accidents and on the response actions
emergency resources used	no/less than 3/more than 3	The more emergency resources used, the larger the probability is that the people or the ship can be saved
number of people in distress	Less than 3/from 3 to ten/more than 10	This is classified according to the incident level issued by the MoT
ship type	cargo ship/dangerous cargo ship	Dangerous ships have a higher propensity to cause pollution
gross tonnage (t)	Below 500/from 500 to 1000/more than 1000	This is classified according to the accident consequence issued by the MoT
arrival time of tug	less than 15 min/30 min	This is the requirement on the response time given by the MSA
position of accidents	Restricted area/fairway	Restricted areas have significant impact on the

		feasibility of response actions
pollution	yes/no	Pollution is a type of economic loss
economic loss	negligible/minor/major/catastrophic	This is determined according to the accident consequence issued by the MoT
loss of ship	yes/no	Loss of ship will cause economic loss
consequence of collision accidents	negligible/minor/major/catastrophic	This is defined according to definition of the MoT in China

Third, the states of some influencing factors are defined according to the regulations of the MoT (Zhang et al., 2016). Ship tonnage, economic loss and consequences of collision accidents are defined according to the definitions of the MoT of China. Similarly, the number of people in distress and the number of fatalities are also defined in this way as the MoT of China also defined the incident level by using this criterion.

2.4 Use of mutual information for dependence determination

Mutual information is derived from entropy theory, which was first proposed by Shannon and Weaver (1994). This method measures the dependence between two variables, and it has been widely used for such calculations in previous studies (Peng et al., 2005). Define X and Y as two random variables. The mutual information of these two variables can be calculated by using Eq. (1)

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} P(x,y) \log_2 (P_{xy}(x,y) / (P(x)P(y))) \tag{1}$$

where $I(X;Y)$ is the joint probability distribution of X and Y, while $P(x)$ and $P(y)$ represent the marginal probability distributions for X and Y, respectively. The relationship between the entropy and mutual information is as follows. The mutual information is the overlap entropy between two random variables and can be defined as Eq. (2) and can be simplified as Eq. (3).

$$I(X;Y) = H(X) - H(X \mid Y) \tag{2}$$

$$I(X;Y) = H(X) + H(Y) - H(X,Y) \tag{3}$$

where $H(X)$ is the entropy of the variable X, $H(Y)$ is the entropy of the variable of Y, and $H(X,Y)$ is the joint entropy, while $H(X \mid Y)$ is the conditional probability. This can also be illustrated as in Figure 2.

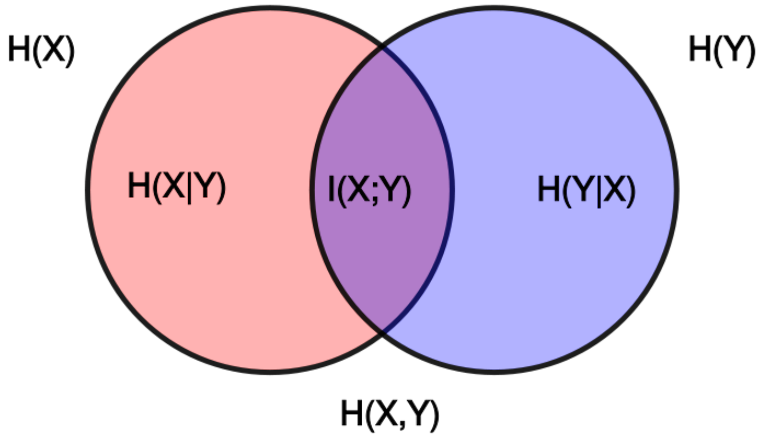

Fig. 2 Diagram for the relationship between mutual information and entropy

According to the mutual information theory developed by Shannon and Weaver (1994), if the mutual information is zero, these two factors are totally independent; if the mutual information is one, these two factors are totally dependent. However, in practice, it is very difficult to find two totally independent or dependent factors. Therefore, the threshold, ℓ, is introduced to determine the dependence of two factors such that if the mutual information satisfies the inequality equation, $I(X;Y) < \ell$, these two factors are assumed to be independent.

2.5 Establish the CPTs for economic loss to facilitate the consequence estimation

The consequence of accidents is a combination of economic loss, gross tonnage and fatalities according to the definition of the MoT in China (Zhang et al., 2016). The economic loss should be assessed because there are no records of such data in the historical data. After an investigation with the staff at the MSA, the loss of ship, gross tonnage and pollution should be utilized to estimate the economic loss. However, it can be seen from Table 1 that the pollution and loss of ship are all recorded by using the linguistic terms of “yes” or “no”. This is too ambiguous to make an assessment of economic loss. Therefore, further analysis is carried out to obtain the CPT for economic loss.

First, the volume of an oil spill can be derived from the historical data. There are two types of such data. One is from a research study in Portugal in which the researchers concluded that approximately 89% of the incidents involved quantities of less than 7 tons of oil, 8% between 7 and 700 tons and only 3% were above 700 tons (Gouveia and Guedes Soares 2010). Another data source is from research in China in the 1990-2010 period (Xiong et al., 2015), where each ton of such oil is valued at approximately 3k RMB. However, the clean-up cost should also be considered in this estimation. Several studies have been carried out to estimate such costs in the literature (Montewka et al., 2013; Xiong et al., 2015; Li et al., 2016); however, as this paper does not focus on accurate clean-up costs, after the investigation with the MSA staff, the clean-up cost is estimated to be more than two times the oil price. By introducing the abovementioned data and assumptions, the economic loss caused by pollution can be estimated and is shown in Table 2.

Table 2 Estimated economic loss of pollution

Oil spill size	Probability	Oil price (ton)	Clean-up cost (ton)	Total pollution cost (ton)
Less than 10	90%	3k	7k	Less than 100k
50 than 300	3.5%	3k	7k	500k to 3,000k
300 to 500	3%	3k	7k	3,000k to 5,000k
Over 500	3.5%	3k	7k	Over 5,000k

Another economic loss, which is caused by the loss of a ship, should also be estimated. From the historical data, 80 ships were lost among the 797 navigational accidents on the Yangtze River. For further analysis, 36% of them are less than 500 gross tonnage (gt), 44% are from 500 to 3,000 gt, and 20% are over 3,000 gt.

Based on the two investigations on economic loss, experts were invited to make offer the advice and judgements to obtain the CPT. In this research, three staff members from the MSA are invited, two experts have bachelor's degrees in marine engineering and have worked for at least eight years (i.e., one worked eight years, another 12 years), the other expert had a master's degree in marine engineering and worked for five years. When making assessments, the well-known extended if-then scheme, which has been widely used in previous studies (Wu et al., 2017b), is adopted. The CPT for economic loss is established as shown in Table 3.

Table 3 CPT for economic loss

pollution	yes	
Loss of ship	yes	no

Gross tonnage	Less 0.5k	0.5 k to 3k	over 3k	Less 0.5k	0.5k to 3k	over 3k
Less than 100k	0.1	0	0	0	0	0
From 100k to 200k	0.3	0.1	0	0.5	0	0
From 200k to 500k	0.3	0.3	0	0.4	0.5	0
From 500k to 3,000k	0.3	0.3	0.3	0.1	0.4	0.4
From 3,000k to 5,000k	0	0.3	0.3	0	0.1	0.4
Over 5,000k	0	0	0.4	0	0	0.2
pollution			no			
Loss of ship		yes			no	
Gross tonnage	Less 0.5k	0.5 k to 3k	over 3k	Less 0.5k	0.5k to 3k	over 3k
Less than 100k	0	0	0	0.1	0.1	0
100k to 200k	0.1	0.1	0	0.6	0.4	0.2
200k to 500k	0.6	0.4	0.2	0.3	0.4	0.5
500k to 3,000k	0.3	0.4	0.5	0	0.1	0.2
3,000k to 5,000k	0	0.1	0.2	0	0	0.1
Over 5,000k	0	0	0.1	0	0	0

3 Application of the proposed BN on the Yangtze River

3.1 Calculation of the mutual information for influencing factors

During 2006-2013, there were 797 navigational accidents on the Yangtze River. These data are from the Jiangsu MSA, which is located in the downstream area of the Yangtze River. Among these data, collision accidents account for 82.8%, while grounding accidents account for 17.2%. To obtain all the mutual information between the influencing factors, the mutual information is calculated one by one. In Subsection 2.4, the mutual information between “gross tonnage” and “time of day”, which are two independent factors, was used as an illustrative example for this calculation process. The other mutual information can also be derived in the same way. For sake of brevity, only an example of two dependent factors, which are “number of people in distress” and “ship type”, are introduced in detail. The CPT for these two factors with their marginal probabilities is shown in Table 4.

Table 4 CPT for “ship type” and “people in distress” with marginal probability

factors	less than 3	4 to 10	more than 10	marginal probability for “ship type”
dangerous cargo ship	0.0010	0.08	0.0093	0.0903
passenger ship	0.0010	0.0001	0.0052	0.0063
cargo ship	0.5052	0.1945	0.2036	0.9034
marginal probability for “people in distress”	0.5072	0.2746	0.2182	1

The mutual information between these two factors in different states can be calculated, which is shown in Table 5. It can be seen from this table that the mutual information for these two factors is 0.1848; in this paper, the threshold is set as 0.05. Therefore, these two factors are assumed to be dependent.

Table 5 Mutual information between "ship type" and "people in distress"

Mutual information	$I(x_1;y_j)$	$I(x_2;y_j)$	$I(x_3;y_j)$
$I(x_i;y_1)$	-0.0017	0.0407	-0.0030
$I(x_i;y_2)$	-0.0005	-0.0001	0.0030
$I(x_i;y_3)$	0.0214	0.1222	0.0029
$I(X_i;Y)$	0.0193	0.1627	0.0029
$I(X;Y)$		0.1848	

After calculating the mutual information among all the influencing factors, the mutual information matrix is obtained and shown in Table 6. Note that as there is no data for the economic loss, a substitute method was introduced for the establishment of the CPT for this node, this factor is not used in this process. Similarly, as the consequence of navigational accidents is defined by the MoT, this node is also not used for the calculation. Note that for this table, the abbreviations are used, and the meanings are as follows: GT (gross tonnage), VB (visibility), ND (number of people in distress), ST (ship type), NF (number of fatalities), ERU (emergency resourced used), TD (time of day), PL (pollution), AT (arrival time of the tug boat in normal conditions), PA (position of accidents), LS (loss of ship). Note that "ship owner" is used as an example to illustrate that the mutual information is useful in identifying the irrelevant factors, although this factor has a relationship with the occurrence of maritime accidents in the midstream of the Yangtze River (Zhang et al., 2013).

Table 6 Mutual information matrix for influencing factors of navigational accidents

factors	VB	ND	ST	NF	ERU	TD	PL	AT	PA	LS	SO
GT	0.00	0.02	0.03	0.04	0.02	0.03	0.02	0.00	0.00	0.03	0.00
VB		0.00	0.00	0.12	0.04	0.05	0.00	0.04	0.00	0.02	0.00
ND			0.18	0.31	0.04	0.11	0.01	0.00	0.01	0.00	0.01
ST				0.04	0.05	0.03	0.11	0.00	0.00	0.01	0.00
NF					0.14	0.02	0.00	0.01	0.02	0.00	0.00
ERU						0.02	0.04	0.04	0.02	0.05	0.01
TD							0.01	0.00	0.00	0.01	0.01
PL								0.04	0.02	0.00	0.00
AT									0.05	0.13	0.00
PA										0.11	0.00

As this paper defines the threshold as 0.05 to determine whether two factors are dependent or independent, it can be seen from Table 6 that several factors are dependent. The ship type is dependent on the number of people in distress; this is because passenger ships have more people in distress, while there are only the crewmembers on the other types of ships (Montewka et al., 2014). The number of fatalities is dependent on the visibility and the number of people in distress because visibility will influence the search and rescue operation and the more people there are in distress, the larger the probability is that people will not to be saved due to limited resources (Wu et al., 2017; Jasionowski, 2011). The emergency resources used depends on the number of fatalities because of the ineffectiveness of the search and rescue operations in emergency responses (Zhang et al., 2014). Pollution is related to the ship type because oil tankers or chemical ships may cause large volume spills (Yip et al., 2011). The loss of ship is related to the arrival time of the tug boat and the position of accidents. On the one hand, if the ship cannot arrive in a limited time, the ship accidents may develop into flooding or other types of accidents (Montewka et al., 2014; Mazaheri et al., 2014). The navigational accidents for the study occurred on the Yangtze River which has many bridges, if the accident position is near a bridge area, attempts to save the ship may not be carried out because of the risk of colliding with bridges.

3.2 Establishment and validation of the qualitative part of the BN

After obtaining the mutual information between all the influencing factors, their relationships can also be derived. It should be mentioned that only the relationship can be obtained; however, the direction of the influence diagram cannot be derived by using mutual information. In other words, the mutual information cannot be used to judge which is a parent node or a child node. Therefore, previous studies and expert opinions should be used to define the direction of the influence diagram.

From the mutual information, “time of day”, “number of fatalities” and “ship type” are related to the number of people in distress. From the previous works and accident development logic, as people are asleep during the night, the number of people in distress will be more than during the day (Jasionowski, 2011), and evacuations at night are also more difficult than during the day; therefore, the “time of day” will influence the “number of people in distress”, which means that the “time of day” should be a child node and the “number of people in distress" is a parent node. In another case, "the number of people in distress" is the child node for "number of fatalities" because the people in distress have a probability of being saved, and the number of fatalities is the number of people in distress minus the number of people saved. Similarly, all the other parent and child nodes can be defined, and the reasons are shown in Table 7. After defining the relationships among the influencing factors, the graphical structure of the BN can be obtained and is shown in Figure 3. It can be seen that in this figure, both the nodes and arcs have been defined. Note that when using a basic BN (Zhang et al., 2012), the relationship between any pair of nodes should be determined by using a set of relationship values, specifically, direct, not direct, uncertain, and reverse direct. It will take a long time for experts to assess these relationships; however, by introducing the proposed mutual information-based method, only direct or reverse direct relationships should be assessed. Therefore, the proposed method will save a great deal of time and reduce the subjective bias in this process.

Table 7 Define the parent and child nodes for consequence estimation

Parent node	Child node	Reason
Number of people in distress	Time of day	Accident at night will make evacuation difficult (Jasionowski, 2011)
	Ship type	Passenger ships have more people than the cargo ships (Montewka et al., 2014)
Number of fatalities	Number of people in distress	The more people in distress, the larger the possibility of fatalities in the restricted zone (Wu et al., 2017b)
	visibility	Low visibility will influence the SAR actions (Zhang et al., 2014)
	Emergency resources used	The more emergency resources used, the more people will be saved (Wu et al., 2018)
Pollution	Ship type	An oil tanker has a larger probability to cause pollution than other types of ships (Yip et al., 2011)
Loss of ship	Arrival time of tug	The arrival time is essential in the emergency response as the time is limited (Wu et al., 2018)
	Position of accidents	The restricted area (such as a bridge area) will greatly influence the emergency response to the accident (Wu et al., 2017b)
Economic loss	Gross tonnage	Large-sized ships may cause more economic loss (Zhang et al., 2013)
	Pollution	It is one type of economic loss shown in Table 3
	Loss of ship	It is one type of economic loss shown in Table 3
Consequence of navigational	Gross tonnage	The definition of the MoT
	Economic loss	The definition of the MoT

accidents	Number of fatalities	The definition of the MoT

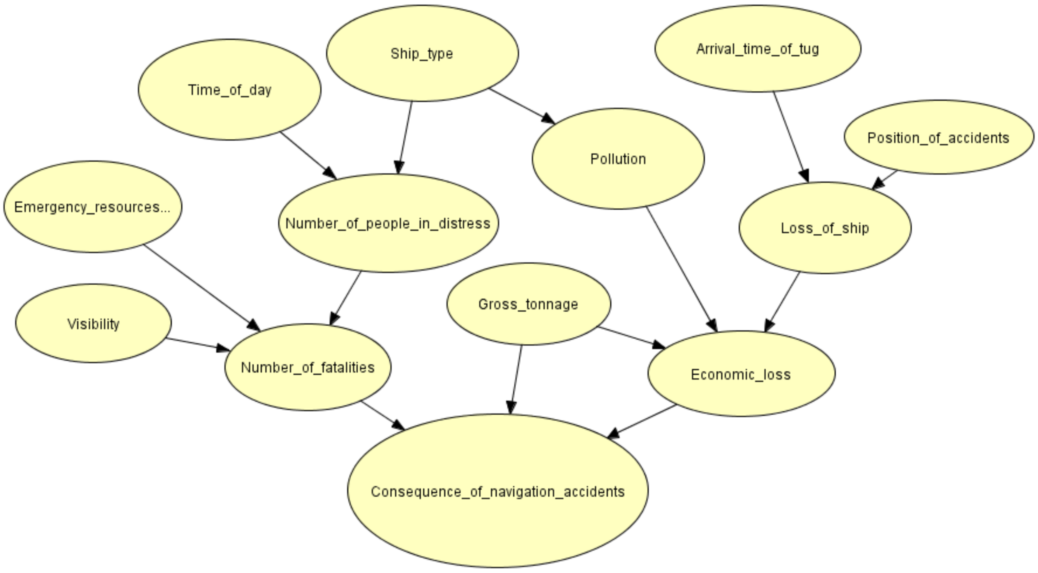

Fig. 3 Graphical structure of the BN for consequence estimation

After the development of the qualitative component of the BN, the graphical structure should be validated to ensure that the nodes are linked by a serial connection, a diverging connection or a converging connection. The d-separation method is used in this paper to validate whether two variables are separated through an intermediate variable, when the two variables are d-separated, the following should be true (Pristrom et al., 2016): 1) The connection is either serial or diverging, and the state of the intermediate variable is known. 2) The connection is converging, and the state of the intermediate variable or any of its descendants is not known. This can be easily carried out by using the Hugin expert software, and the result is shown in Figure 4, which demonstrates that the nodes of the developed BN are d-separated.

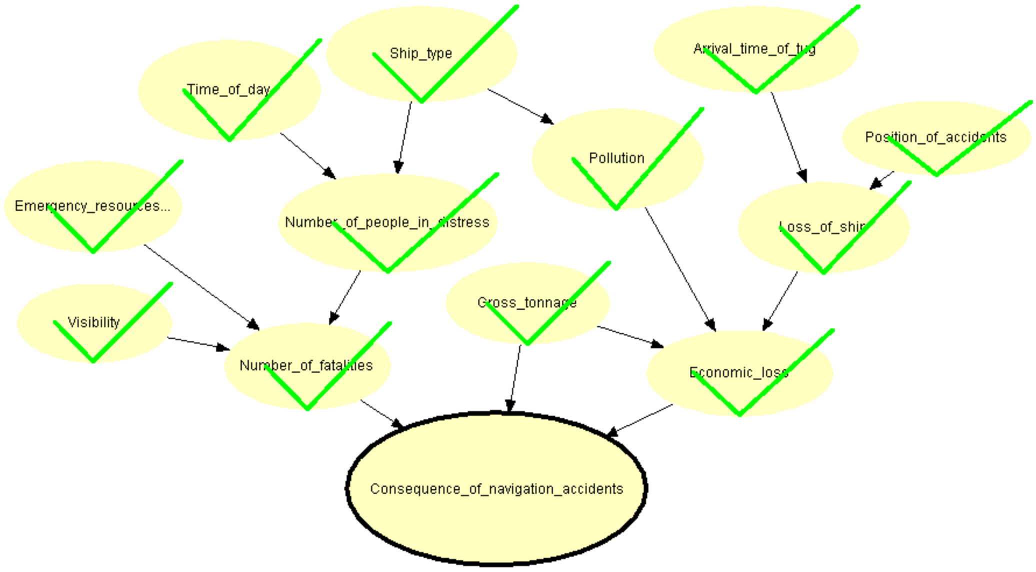

Fig. 4 Results of the d-separation analysis of the developed BN

3.3 Use of the BN for consequence estimation

Before introducing the quantitative part of the BN, the CPT for the consequences of navigational accidents should also be defined. The definition of this CPT is simple because the MoT of China has defined the regulations for this, and the CPT for the consequences of navigational accidents is shown in Table 8. It should be mentioned, for the sake of space, that only part of the CPT is given in this paper, and the states of the number of fatalities are simplified. Specifically, “no” stands for no fatalities, “SI” stands for “serious injury”, “LT2” stands for “1 to 2”, and “O2” stands for “over 2”.

The prior information of the navigational accidents can be derived using the historical data, and they are shown in Table 9. By introducing the prior information, the BN for the consequence estimation of navigational accidents can be obtained, and the result is shown in Figure 5.

Table 8 CPT for consequence of navigational accidents

Economic loss	Less than 100k											
Gross tonnage	Below 500				500 to 3000				Over 3000			
Number of fatalities	no	SI	LT2	O2	no	SI	LT2	O2	no	SI	LT2	O2
Negligible	1	0	0	0	1	0	0	0	1	0	0	0
Minor	0	1	0	0	0	1	0	0	0	1	0	0
Major	0	0	1	0	0	0	1	0	0	0	1	0
Catastrophic	0	0	0	1	0	0	0	1	0	0	0	1

Table 9 Prior information of influencing factors of navigational accidents

Node	State 1	State 2	State 3
time of day	day	night	-

	0.63	0.27	
ship type	cargo 0.90	dangerous 0.09	passenger 0.01
visibility	good 0.79	bad 0.21	-
emergency resources used	no 0.72	1 to 2 0.21	above 3 0.07
arrival time of tug (min)	Less 15 0.71	Less 30 0.29	-
position of accidents	restricted area 0.25	fairway 0.75	-
ship tonnage (t)	below 500 0.3	500 to 3k 0.3	above 3k 0.4

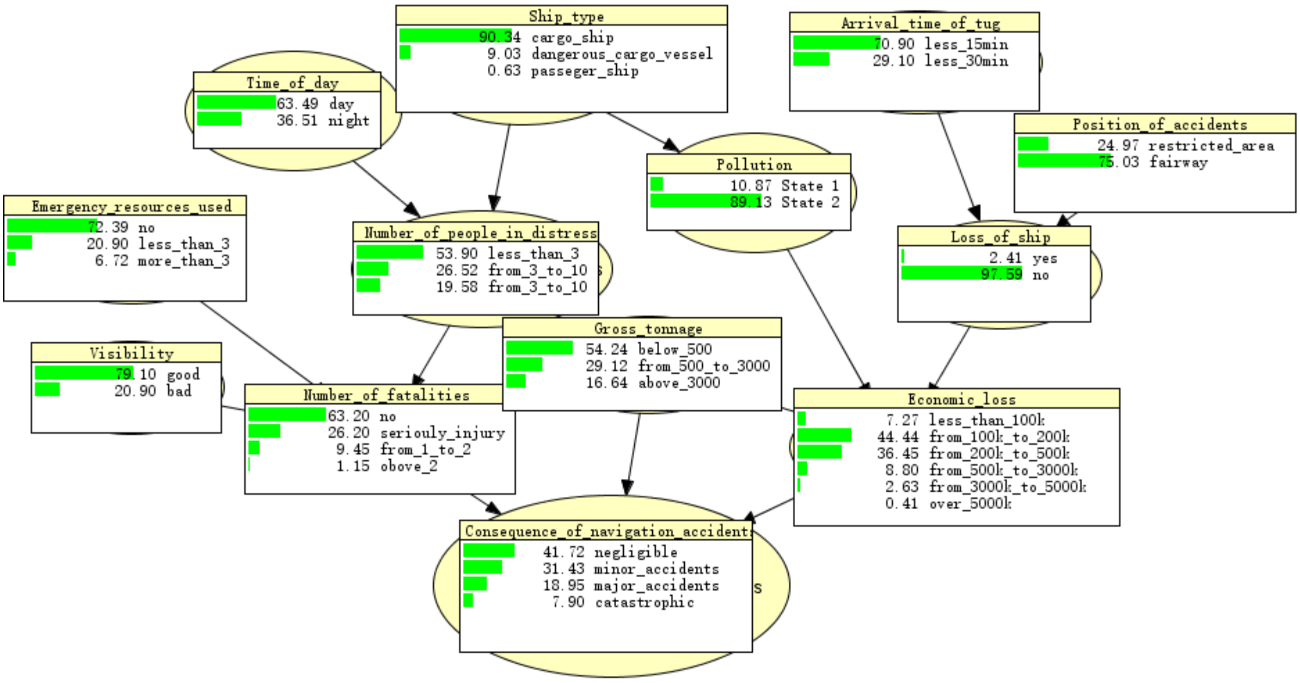

Fig. 5 The BN for the consequence estimation of navigational accidents

It can be seen from Figure 5 that the consequence of navigational accidents is “negligible” with a probability of 0.42, is “minor” with a probability of 0.31, is major with a probability of 0.19 and is “catastrophic” with a probability of 0.08. Although 797 navigational accidents occurred during the 2006-2013 period on the Yangtze River, only 8% of the navigational accidents were catastrophic accidents. The reason for this is that emergency management has played an essential role in reducing the accident consequences (Zhang et al., 2014). As the consequences of navigational accidents is an essential component of a risk analysis in the formal safety assessment framework (Zhang et al., 2013), the decision-maker can use this results to further analyse the safety level on the Yangtze River. By establishing the criteria for the risk levels, the decision-maker can take actions to accept the safety level or improve it. The risk control options, which are also a component of a formal safety assessment, can be further analysed to mitigate the navigational risk by taking countermeasures. However, as this paper intends to develop a practical method for consequence estimation, a further analysis is not carried out.

3.4 Sensitivity analysis for partial validation of the developed model

After deriving the consequences of navigational accidents using a BN, a sensitivity analysis should be carried out to partially validate the quantitative component of the model. This analysis is necessary as some assumptions (i.e., the CPT of economic loss) are used, which may cause uncertainty. Two axioms are often used to validate that the developed model is reasonable (Pristrom et al., 2016; Zhang et al., 2016; Zhang et al., 2013; Akhtar and Utne 2014), and they are as follows.

1. Axiom 1. A slight increase/decrease in the prior probabilities of each parent node should certainly result in a relative increase/decrease of the posterior probabilities of the child node.

2. Axiom 2. The total influence magnitudes of the combination of the probability variations from x attributes (evidence) on the values should always be greater than that from the set of $x-y(y \in x)$ attributes (sub-evidence).

The validation of these two axioms is as follows.

(1) Test of Axiom 1. Taking the "consequence of navigational accidents" as an example, the utility values of severity are defined as $V_1(catastrophic) = 40000$; $V_2(major) = 3000$; $V_3(minor) = 500$; $V_3(negligible) = 200$, respectively, and the consequence is measured as 1000 Yuan. Therefore, the consequence can be estimated by using the equation $I_j = \sum_{i=1}^{N} V_i P_i$, where V_i is the utility value, P_i is the associated probability of V_i, and N is 4 as there are four types of severities. When increasing the values of "serious injury" (i.e., one state of the number of fatalities) by 10% and 20%, the consequence of the navigational accidents increases from 3969 to 3976 and 3981, respectively. Similarly, the other nodes can also be validated as following Axiom 1.

(2) Test of Axiom 2. When each sub-evidence of “emergency resources used = more than 3”, “visibility = bad”, and “number of people in distress = from 3 to 10” is entered, the consequence of navigational accidents is 5100, 4376 and 4794, respectively. When “emergency resources used = more than 3”, “visibility = bad”, and “number of people in distress = from 3 to 10” are entered into this model, the consequence of navigational accidents is 7498. Further tests have also been undertaken for other nodes (e.g., economic loss), and the results reflect that the model follows Axiom 2.

3.5 Results analysis of catastrophic accidents

From Figure 5, there are 8% catastrophic accidents among 797 navigational accidents. To validate this result, the catastrophic accidents in the Yangtze River were collected during the 2006-2013 period. From the statistical analysis, 8 accidents caused more than 2 fatalities. The detailed information on these accidents is shown in Table 10.

Table 10 Detailed information on navigational accidents that caused over two fatalities

No.	Ship tonnage (t)	Time of day	Position of accident	Number of people in distress	Fatalities	Emergency resources used	Visibility	Arrival time of tug (min)	Accident type
1	209	Day	No. 153 black buoy	8	3	11	Good	Less than 30	Collision
2	404	Night	Nanjing No. 136 buoy	4	2	3	Good	Less than 15	Collision
3	500	Night	No. 107 red buoy	4	2	11	Good	Less than 30	Collision
4	2972	Night	No. 54 buoy	14	2	3	good	Less than 30	Collision
5	1893	Night	Sutong Bridge area	9	2	10	Bad	Less than 15	Collision
6	5719	Night	No. 150 buoy	25	2	2	Bad	Less than 30	Grounding
7	19983	Day	No. 96 black buoy	8	2	2	Bad	Less than 30	Grounding
8	860	Night	No. 30 buoy	7	2	1	Good	Less than 30	Grounding

However, only 1% of the navigational accidents caused more than 2 fatalities because the other 7% of catastrophic accidents are caused by economic loss; this can be observed from Figure 5. Therefore, by analysing the catastrophic accidents, the estimated accident consequence is close to the real accident data, which demonstrates that the consequence estimation result has good accuracy. It can also be deduced that the majority of catastrophic accidents are caused by economic loss (8 times of the number of catastrophic accidents caused by fatalities). In practice, a comprehensive assessment of the accident consequence should be carried out, not only considering the fatalities but also the economic losses. From the historical data, there are approximately 20 ships that have been lost and 83 pollution accidents. These are also close to the historical data, and they will be discussed in detail in the discussion section to illustrate that the proposed model achieves a high accuracy.

3.6 Predominant factors analysis of navigational accident consequence

A predominant factor analysis is essential to discover which factors influence the consequence of navigational accidents most; therefore, countermeasures can be focused on these factors to improve maritime safety. From a previous study (Hänninen and Kujala 2012), this analysis is often carried out in risk modelling by using a BN, and the principles of this analysis will not be presented detail. To discover the predominant factors for the consequence of navigational accidents, the Hugin Expert software is introduced, and the values of the information module of this software are used to facilitate the calculation process. The analysed results are shown in Figure 6. Note that only the input variables are analysed while the intermediate nodes are ignored because the decision maker can only take countermeasures on the input variables.

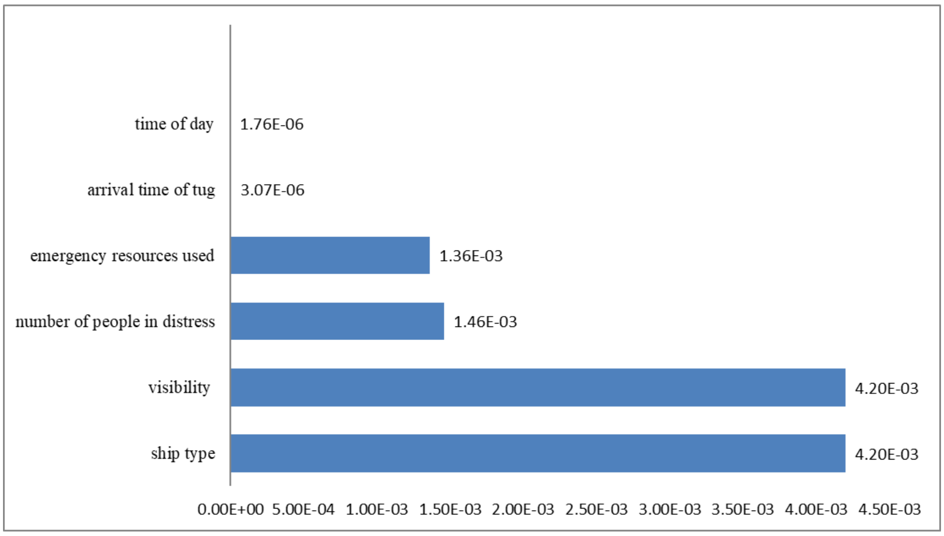

Fig. 6 Predominant factor analysis of the consequences of navigational accidents

From Figure 6, it can be seen that four factors have the most influence on the consequences of navigational accidents, which are ship type, visibility, number of people in distress, and emergency resources used. Ship type is an essential factor because a passenger ship will cause more people in distress than other types of ship, which is also an important factor for the consequence of navigational accidents. A dangerous cargo ship may have a relatively high probability of causing pollution. Low visibility will have a crucial impact on navigational safety and the search and rescue operations. The more people there are in distress, the greater the probability is of fatalities in maritime accidents. Emergency resources can help to save lives after accidents, and this can also reduce the severity of the accident consequences. Based on this analysis, the maritime safety administration, which is in charge of maritime safety in China, can take countermeasures such as "paying more attention to passengers and dangerous cargo ships", "prohibit ship navigation when the visibility is low" and "develop more emergency facilities along the Yangtze River" to reduce the severity.

4 Discussion

By introducing mutual information, this paper proposes a modified BN for the consequence estimation of navigational accidents. Compared with the basic BN (Zhang et al., 2012), this proposed method uses mutual information to judge the independence of the influencing factors, from which the parent nodes and child nodes can be defined. The merit of this method is that it can reduce the subjective judgements in the modelling process because the traditional BN uses expert judgements for defining the graphical structure (Wu et al., 2017b; Hänninen and Kujala 2014), while the proposed method uses the data, and this is the aim of this paper. However, compared with the traditional mutual information-based BN (Yang et al., 2018), which requires adequate data for modelling, expert judgement is required for this proposed method.

The advantages and disadvantages of these three methods are shown in Table 11. It can be seen that the proposed method and the basic BN can describe the accident development very well, while the traditional mutual information-based method can also describe it well when the dataset describes the accident development adequately. The validation of the traditional mutual information method is convincing as it agreed with the results from the data, while the validation of the basic BN and proposed BN is only reasonable as it uses expert judgements. The applicability of the traditional mutual information-based method is very good if the dataset is adequate, while the other two methods can also be flexibly applied to other scenarios.

Table 11 Comparison among the three types of BN methods

Items	**Basic BN (Zhang et al., 2012)**	**Traditional mutual information BN (Yang et al., 2018)**	**Proposed mutual information-based BN**
Expert judgement	Required	Not required	Partly required
Accident development description	Good	Good if with detailed description	Good
Validation of the model	Use axioms and reasonable	Use data and discussion	Use axioms and reasonable
Applicability	Good	Good if dataset is adequate	Good

However, the economic loss is lacking from the historical data, and this node is introduced to facilitate the consequence estimation by using expert inputs and the existing data to derive the CPT rather than the relationships. However, in practice, if these data can be collected, the quantitative component of this node can also be derived by using the mutual information-based method. The node for consequences of navigational accidents is derived from the regulations of the MoT of China; similarly, this node can also be obtained by using mutual information. However, this also verifies that the BN is flexible in that it can use both historical data and subjective judgements in the modelling process.

From the results analysis of the developed BN, the results are reasonable and can be used for the consequence estimation for navigational accidents for three reasons. First, the fatalities of more than 2 are approximately 1%, which is the same as the historical data. Because eight navigational accidents caused more than two fatalities, which is shown in detail in Table 11, this result is very close to the predicted result ($1\% \times 798 = 8$). Second, from the historical data, there are approximately 20 ships that have been lost, although there is a slight difference from the prediction result ($2\% \times 798 = 16$), the result is also close to the historical data. Third, the historical data on pollution accidents (83) are also close to the predicted result

($11\% \times 798 = 88$). Although there is no record on the economic loss, which makes the result difficult to validate using historical data, this result should be reasonable because the three factors have been verified by using historical data.

Note that it is hard to validate all the obtained outcomes. Background knowledge is often used in the risk modelling process (Aven 2010; Mazaheri et al., 2014; Goerlandt and Montewka 2015). However, background knowledge is not equally available to understand the interactions among all the parts of the system (Montewka et al., 2014) and will finally cause uncertainty. In practice, it is inevitable to simplify assumptions, which will also cause uncertainty. In this paper, the historical data on fatalities, ship loss and pollution are used for validation, and the analysed results are close to the statistical data, which has been discussed in the previous paragraph. Therefore, the results can be assumed to be reasonable, especially for the "major" and "catastrophic" severity accidents. The deficiency is that there are no records on the economic loss and expert opinions are used for the derivation of the CPT to facilitate the modelling process, which makes it difficult to validate if the severity of "negligible" and "minor" are appropriate. However, from the perspective of an accident analysis, the "major and "catastrophic" accidents should be prevented and given more attention than the "negligible" and "minor" accidents, and this result can also be assumed to be reasonable from this practical aspect.

5 Conclusions

The main contribution of this paper is to propose a mutual information-based BN method for consequence estimation of navigational accidents in the Yangtze River and to identify the predominant factors for such accidents. First, the influencing factors for the consequence of navigational accidents are identified from the historical data and previous works. Second, the mutual information is utilized to judge the independence of the influencing factors, and then, the graphical structure of the BN can be derived. Finally, the CPTs are established by using the historical data. Because the traditional BN often uses expert judgements to define the graphical structure of the BN, this paper utilizes the mutual information to reduce the subjective impact on the consequence estimation. By applying this mutual information-based BN to consequence estimation, four predominant factors for the consequence of navigational accidents can be identified: ship type, visibility, number of people in distress, and emergency resources. Based on these findings, countermeasures can be taken to reduce the consequences of such accidents.

Although this paper uses the Yangtze River as a case study, the proposed model is readily applied to other waterways to predict the consequences of maritime accidents if the data in the applied waterways have similar characteristics Specifically, if the majority of the data are available for modelling, while some data is missing from the dataset the process presented may still be used. However, it should be mentioned that when applying this method to other waterways for consequence estimation, the influencing factors should be carefully handled because the Yangtze River is an inland waterway transportation route. Moreover, the CPTs developed in this model should also be updated when applying to other waterways. However, the mutual information-based method can be applied to determine the dependencies of the influencing factors if the historical data have been collected in detail.

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