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Use of fuzzy fault tree analysis and Bayesian network for occurrence likelihood estimation of navigational accidents in the Qinzhou Port

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Abstract: This paper utilizes a fuzzy fault tree analysis and Noisy-OR gate Bayesian network to estimate the occurrence likelihood of navigational accidents. The kernel of this proposed method is first to construct the fault tree from investigation reports of navigational accidents, to calculate the occurrence probability of basic events using fuzzy set, to transform the fault tree to Bayesian network using the Noisy-OR gate. The merit of the developed model can overcome the problem of absolute description of the relationships between basic events and intermediate events. Finally, the model is applied to Qinzhou Port, the results are reasonable by comparing the results in other waterways. Moreover, the key influencing factors are identified from minimum cut set analysis and sensitive influencing factors are quantified sensitivity analysis. Consequently, the findings are beneficial for the maritime authorities to take countermeasures for navigational accidents prevention.

Key words: Fuzzy fault tree analysis, Noisy-OR gate, Bayesian network, risk assessment, maritime transportation

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1 Introduction

Collisions and groundings (i.e. navigational accidents) are the most frequently occurring type of maritime accidents, which accounts for approximately 85%. From the statistical analysis (Eleftheria et al., 2016; Yip, 2008; Zhang et al., 2013), the occurrence likelihood of navigational accidents ranks first among all types of maritime accident. Specifically, in the Istanbul Strait, the occurrence likelihood of navigational accidents accounts for 69% among all types of accidents from fifty years of survey (Akten, 2004). Similarly, in the port area, the navigational accident occurs frequently due to the high traffic density (Mou et al., 2010) and complexity of marine traffic (Wen et al., 2015;Westrenen and Ellerbroek 2017). In the Gulf of Finland, the occurrence likelihood of the navigational accident accounts for 74% in the majority of years from 2007 to 2008 (Maria et al., 2014). In Hong Kong Port, the occurrence likelihood of this type of the navigational accidents account for 63% (Yip, 2008); and in Tianjin Port, the occurrence likelihood of this type of accident accounts for 86.29% (Zhang et al., 2016). In the Yangtze River, the occurrence likelihood of this type of the navigational accident account for 58.87% (Zhang et al., 2013).

Owing to the relatively high occurrence probability and serious consequence, many studies have focused on the occurrence likelihood estimation of this type of accident. In terms of collisions, Arici et al. (2020) utilized the fuzzy bow-tie method to estimate the collision in ship to ship (STS) operations, and analysed the factors that have the strongest relationship with collision/contact accidents in STS operations. Szlapczynski and Szlapczynska (2016) defined the domain-based collision risk parameters: degree of domain violation (DDV) and time to domain violation (TDV) for estimating the occurrence likelihood of ship collision risk. Ugurlu et al. (2020) analysed the occurrence likelihood of collisions by using Geographic information system, human factor analysis and classification system (HFACS), and Bayesian network model in the Black Sea. Li et al. (2020) forecasted the occurrence likelihood of navigation risk by using weighted basic probabilistic assignment and matrix operation. In terms of groundings, the majority models for evaluating the occurrence likelihood are based on investigation reports of accidents or incident and statistical data (Bye and Aalberg 2018; Mazaheri et al., 2016). Mazaheri et al. (2016) presented an evidence-based and expert-supported approach to assess the occurrence likelihood of ship-grounding accidents. Wu et al. (2019) proposed a mutual information-based Bayesian network method for estimating the consequences of navigation accidents and identified the predominant factors of navigational accidents. Jiang et al. (2021) utilized the analytical model to estimate the occurrence likelihood of a ship being grounded in the fluctuating backwater zone.

From the previous studies, Bayesian networks (BN) are widely used for risk assessment due to its intuitive graphical structure and quantitative representation of the relationships between influencing factors from a probabilistic perspective (Akhtar and Utne 2014; Chen et al., 2019; Khakzad et al., 2013; Wang and Yang 2018). The advantages of this method are as follows. Firstly, BN could be used to intuitively represent the accident development process (Baksh et al., 2018; Cheng et al., 2021). Secondly, BN is flexible to consider uncertainty in the dependencies among the influencing factors (Afenyo et al., 2017). Thirdly, the posterior probability of each event can be updated by using the new information (Mazaheri et al., 2016). Fourthly, BN could compensate for data scarcity and adjust the entire structure by changing only a few variables (Pristrom et al., 2016). Fifthly, sensitivity analysis can be used to identify the key influencing factors (Zhang et al., 2016), which are useful for safety management of maritime transportation.

Although there are several merits of the BN, the quantitative part of the BN requires a large amount of historical data to determine prior probabilities and conditional probability tables. In practice, owing to lack of data, expert judgements are often requested and CPTs are obtained through expertise. Mokhtar et al. (2016) determined the conditional probability of every BN node by using expert knowledge. Wang et al. (2017) and Abimbola et al. (2015) calculated failure probability by using the relationships of logical "OR" and "AND" gates to define conditional probability distribution. However, the probabilities of the root node and conditional probabilities table derived from expert opinion might include subjective elements, in addition, logic gate analysis is absolute, and the occurrence of a failure event is not simply binary (e.g. a '1' occurs and a '0' does not occur) (Feng et al., 2020).

To overcome these limitations, fuzzy fault trees and Noise-Or gate are introduced to address the problem of absolute description of conditional probabilities. Moreover, as fuzzy fault trees can well describe the accident development using historical data, it is introduced to obtain basic events and associated prior probabilities. Wang et al. (2013) and Arici et al. (2020) used fuzzy fault trees to obtain accident occurrence probabilities, Feng et al. (2020) and Xu et al. (2019) used the Noisy-OR gate BN to achieve the CPTs with small data sets, they found that the fuzzy fault tree was useful for the acquisition of accident occurrence probabilities.

The objective of this paper is to construct a risk assessment model, which can be used for analysing navigational risk in a systematic way by transforming the fault tree to the BN. The remainder of the paper is organized as follows. The probabilistic model for estimating the occurrence likelihood of navigational risk is developed in Section 2. Section 3 applies the newly developed method to the Qinzhou Port. Results and discussion are carried out in Section 4, and Conclusions are drawn in Section 5.

2 Development of the FFTA-Bayesian network based navigational risk assessment model

2.1 Establish a navigational risk assessment framework

The proposed navigational risk assessment framework is shown in Figure 1. The modelling process can be summarized in the following three steps.

The first step is to construct the fault tree and calculate the probability of the basic events (BEs). In this step, the influencing factors for navigational accident are identified from the historical data and previous studies. Afterwards, the relationships between the influencing factors are obtained by using accident investigation reports. Finally, the fault tree model is developed, and the probability of the basic events for navigational accident are derived by using fuzzy set.

The second step is to transform the fault tree into the graphical structure of Bayesian network. Specifically, basic event is treated as root node, intermediate event (IE) is treated as intermediate node and top event (TE) is treated as top node. The conditional probabilities of the intermediate nodes are derived using Noisy-OR gates.

The third step is to estimate occurrence probability of navigational accidents using Bayesian network. Minimum cut set and sensitivity analysis are carried out in the developed Bayesian network for navigational risk assessment.

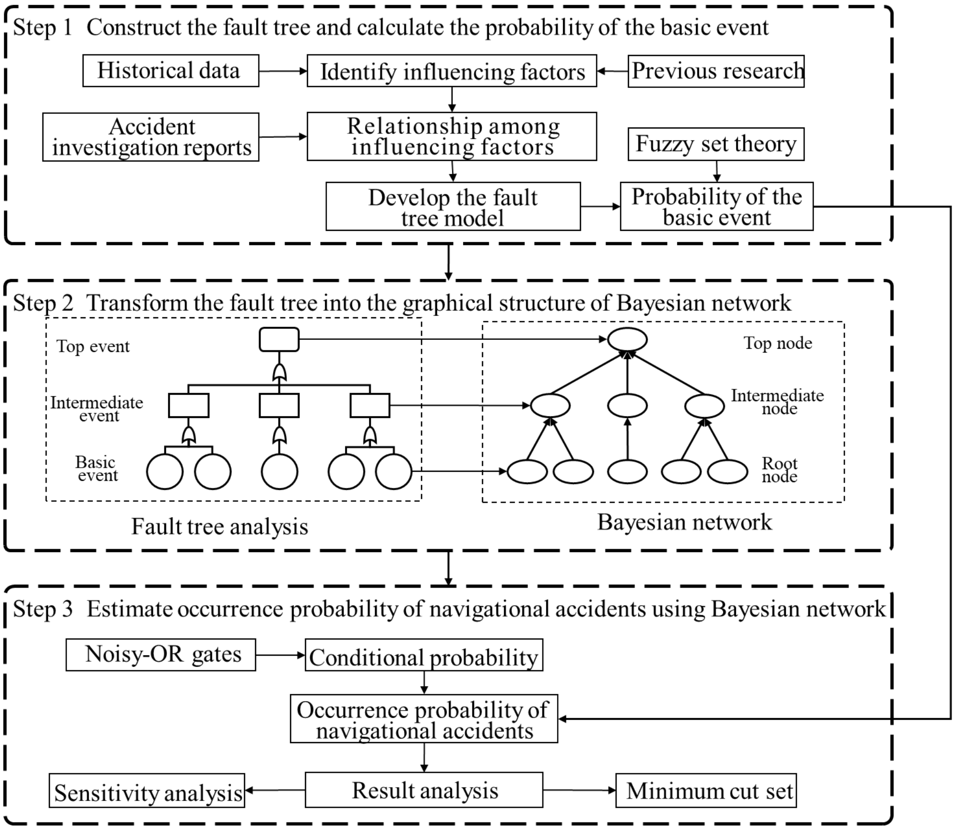

Figure 1 Developed framework for Navigational risk assessment

2.2 Identify the influencing factors to develop the fault tree of navigational accidents

Fault Tree Analysis (FTA) is a top-down deductive failure analysis method that uses Boolean logic to combine lower order events to analyse undesired states in a system. Fault trees can analyse not only system failures caused by a single factor, but also system failures caused by multiple factors with different conditions (Wang et al., 2013). Owing to intuitiveness, concision, visualization and predictability of FTA (Ding and Yu 2005; Fay, 2003; Li and Huang 2012), it has been widely used in maritime field (Zhang et al., 2019; Guan et al., 2016; Sakar et al., 2021a). In a fault tree, it includes top events, intermediate events and basic events, which are developed by logic gates.

To identify the influencing factors (basic events), the historical data of maritime accidents are collected in Qinzhou port from the Maritime Safety Administration of Guangxi, which are 115 cases from 2018 to 2020. In addition, previous studies are also used to determine influencing factors, which are given in Table 1. The reasons of choosing these influencing factors are descried in detail as follows.

1. Top Event (TE). The navigational risk is treated as the top event of the fault tree, which is also the objective of this paper.

2. Intermediate Events (IE). The intermediate events will be introduced to facilitate the modelling process. Traditionally, the influencing factors of navigational accidents can be categorized into three types, which are channel environment (IE1, Roeleven et al., 1995; Stahlberg et al., 2013b), wharf environment (IE2, Xia, 2021), and emergency resource (IE4, Wu et al., 2019; Zhang et al., 2019). Moreover, traffic complexity has been proved to be a key influencing factor of navigational risk (IE3, Mazaheri et al., 2014; Mullai and Paulsson 2011; Wang et al., 2019). Therefore, these four factors are treated as the intermediate events in this paper.

3. Basic Events (BE). Navigational environment includes the channel environment and wharf environment. Channel environment includes lack buoys, fish cage, turning circle of channel, shallow area in curved channel etc, which are analysed from the collected accident reports in the Qinzhou Port. Wharf environment is particularly important, which includes bottom elevation between wharfs and actual ship tonnage exceeds design, etc. Ship traffic is also very important since it will increase the probability of collision accidents, therefore, the number of dredging ships, small-sized ships and fishing ships are the primary influencing factors for accidents in these areas. As the location of emergency resources is fixed and cannot be allocated along the channels, the distance between the location of the incident and the tugboat and anchorage will also affect the navigation risk.

To simplify the modelling process, the status of all nodes is treated as binary, 12 BEs and 5 IEs were identified in the FT diagram. According to the historical data and previous studies, all basic events related to collision/grounding during navigation have been listed in Table 1.

Table 1 Identified BEs for navigational accidents in Qinzhou Port

Abbreviation	Basic Event	Descriptions	Frequency	References
BE1	Oyster culture beds	There are around 60 illegal oyster culture beds close to channel waters, the closest beds are only 10 meters away from the approach channel.	7	
BE2	Turning circle of channel	It is required to be greater than 3 times of the length of designed ship, channel of Dahuan and Sandun cannot meet this requirement	5	Debnath and Chin 2009

BE3	Lack of buoys	The channel of Eagle Ridge has not been completed, resulting that 500m waterway lacks buoys	8	Debnath et al., 2011
BE4	Switch of route due to construction	The development of the western channel led to switch of route	8	Zhang et al., 2019
BE5	Inconsistent bottom elevation between wharfs	The bottom elevation of adjacent wharfs is different, which may cause the ship grounding accident.	10	
BE6	Actual ship tonnage exceeds design	The tonnage of some actual ships is larger than the designed tonnage.	15	
BE7	One-way traffic	Due to the limited width of the channel, the Yingling to the Dalanping is a one-way channel, which increases the difficulty of ship navigation.	5	Debnath et al., 2011; Stahlberg et al., 2013b
BE8	Dangerous goods ships	There is a liquefied gas carrier terminal and a crude oil terminal in the Sandun. Dangerous goods ships often navigate in the nearby waterways, which has a significant impact on the navigational risk.	20	Huang et al., 2021
BE9	Dredging ships in the waterway	Around five dredging ships is working in the Sanduan waterway.	9	Zhang et al., 2019
BE10	The number of small-sized ship	The Yingling is a terminal for large-sized container ships, and the cargos needs to be transferred to other terminals by small ships, which increases the traffic density.	10	Debnath et al., 2011; Pietrzykowski, 2008
BE11	Distance of tugboat	The distance of the tugboat to the accident will have a significant impact on the emergency response.	22	Wu, et al.,2021; Zhang et al., 2019
BE12	Distance of anchorage	The distance of anchorage will have a significant impact on the emergency response.	17	Debnath and Chin 2016; Wu, et al.,2021

After defining the TE, IEs and BEs, the fault tree model for navigational risk assessment can be developed, which is shown in Figure 2. In this fault tree model, there are 5 IEs and 12 BEs.

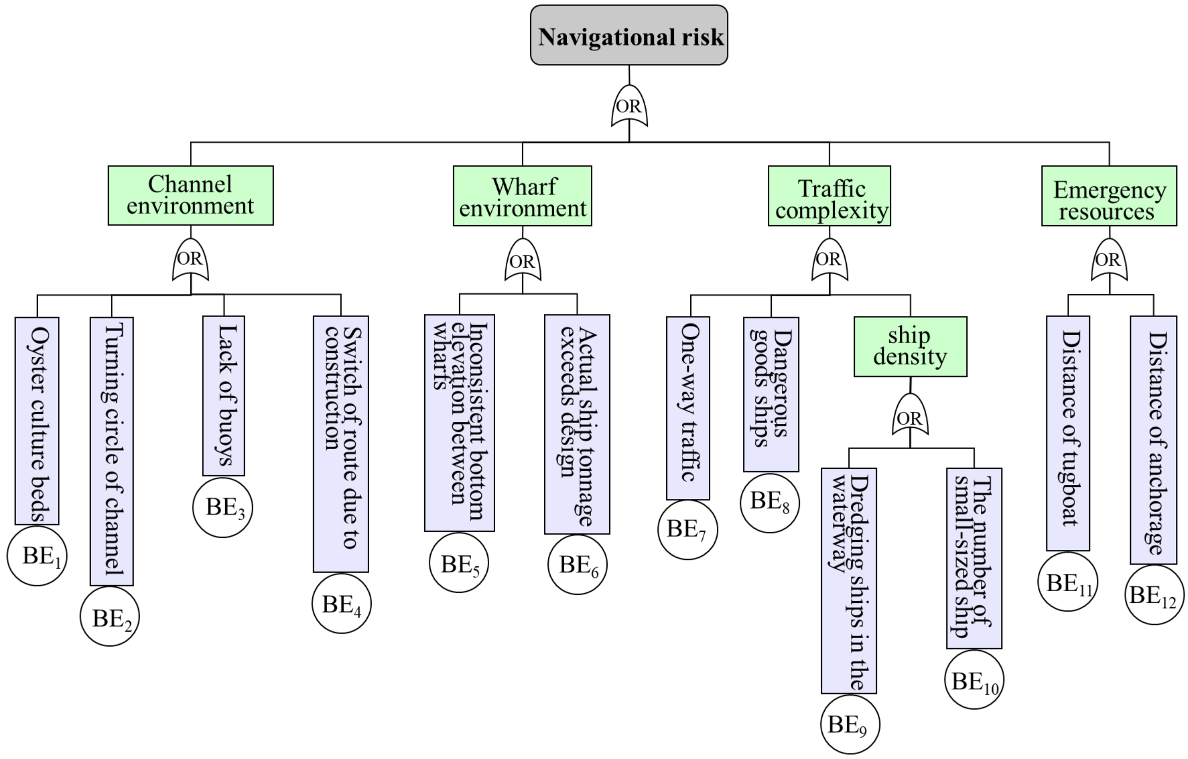

Figure 2 Fault tree model for navigational risk assessment

2.3 Introduce fuzzy set to obtain probability of BEs

After establishing the structure of the FTA, the nest step is to quantify the BEs. Traditionally, it can be obtained by using historical data. However, owing to the scarcity of data, it is hard to directly quantify the BEs from historical data and the expert judgment is the alternative solution. Owing to the ability to deal with uncertain and vague information (Arici et al., 2020; Wu et al., 2018; Wu et al., 2019; Wu et al., 2020), the Fuzzy set theory has been widely used in maritime transportation and it is introduced for quantification of the BEs in this paper. The derivation of the probability of BEs can be achieved in four steps.

(1) Quantify the BEs using triangular fuzzy number. When defining the linguistic term of BEs, there are several types of membership functions, including triangular, trapezoidal and Gaussian shape functions. To simply the modelling process, the triangular fuzzy number, which can be represented by the triple (a_1, a_2, a_3) and the corresponding membership function is written as Eq. (1).

$$\mu_A(\chi)=\begin{cases} 0 & ;\chi \le \mathrm{a}_1 \\ (\chi-\mathrm{a}_1)/(\mathrm{a}_2-\mathrm{a}_1); & \mathrm{a}_1 \le \chi \le \mathrm{a}_2 \\ 0 & ;\chi \ge \mathrm{a}_3 \end{cases} \tag{1}$$

(2) Aggregate the expert judgements on the BEs. Owing to the different experience, background knowledge, the experts may have different judgements on the same BE, therefore, the similarity degree $s(\omega_i,\omega_j)$ between expert e_i and expert e_j should be calculated and it is written as Eq. (2).

$$s(\omega_i,\omega_j)=\begin{cases} EV_i / EV_j, EV_i \le EV_j \\ EV_j / EV_i, EV_j \le EV_i \end{cases} \tag{2}$$

Where $0 \le s(\omega_i, \omega_j) \le 1$, ω_i and ω_j are two triangular fuzzy numbers. EV_i and EV_j are the expectancy evaluation for ω_i and ω_j respectively. The expectancy evaluation of a triangular fuzzy number $\omega_i = (a_1,\ a_2,\ a_3)$ is defined as:

$$EV(A) = \frac{1}{2}[E^-(A) + E^+(A)] \tag{3}$$

where $E^-(A) = (a_1 + a_2)/2, E^+(A) = (a_2 + a_3)/2$

After the comparison, the decision matrix M, which use the $s_{ij} = s(\omega_i, \omega_j)$ as the element can be defined. In his decision matrix, if $i = j$, then $s_{ij} = 1$. Moreover, the average agreement degree $A(E_i)$ of the expert e_i is shown in Eq. (4).

$$A(e_i) = \frac{1}{n-1}\sum_{\substack{i \ne j \\ j=1}}^{n} s_{ij}(\omega_i, \omega_j) \tag{4}$$

Afterwards, the relative agreement degree (RAD) of each expert can be calculated.

$$RAD_i = A(e_i) / \sum_{i=1}^{n} A(e_i) \tag{5}$$

Finally, expert judgements on each BE can be converted into a fuzzy number p_j.

$$x_j = \sum_{i=1}^{m} RAD_i \otimes x_{ij} \quad j = 1, 2, \ldots, n \tag{6}$$

where x_j is the aggregated fuzzy number of BE_j ; x_{ij} is the fuzzy number of BE_j assigned by expert E_i ; m is the number of experts; n is the number of BE_s .

（3）Defuzzify the fuzzy possibility of BEs. The center of area defuzzification method is adopted in this paper because of its simplicity and usefulness, and it is written as Eq. (7).

$$P_{BE}^* = \frac{\int \chi \mu_A(\chi) d\chi}{\int \mu_A(\chi) d\chi} = \frac{\int_{a_1}^{a_2} \frac{\chi - a_1}{a_2 - a_1} \chi d\chi + \int_{a_2}^{a_3} \frac{a_3 - \chi}{a_3 - a_2} \chi d\chi}{\int_{a_1}^{a_2} \frac{\chi - a_1}{a_2 - a_1} d\chi + \int_{a_2}^{a_3} \frac{a_3 - \chi}{a_3 - a_2} d\chi} = \frac{1}{3}(a_1 + a_2 + a_3) \tag{7}$$

where P_{BE}^* is the output of defuzzification of BE; χ is the output variable.

(4) Convert fuzzy possibility score (FPS) into fuzzy probability value (FPV). The method, which has been introduced by Wang et al. (2013), is used to convert the fuzzy probability score into the fuzzy probability value of a basic event, which is shown in Eq. (8).

$$FPV = \begin{cases} \dfrac{1}{10^{K}}, FPS \neq 0 \\ 0 \;\; , FPS = 0 \end{cases} \tag{8}$$

where $K = (\frac{1-FPS}{FPS})^{\frac{1}{3}} \times 2.301$ and $P_{BE}^{*} = FPS$, $P_{BE} = FPV$; P_{BE} is the occurrence probability of the BE.

2.4 Use of Noisy-OR gate Bayesian network to derive the occurrence probability

The traditional FTA utilize logical "OR" and "AND" gates to derive the occurrence probability, this method has two limitations. First, the logical gate analysis is extremely absolute to describe the relationships between BEs and IEs, however, in practice, the relationship is not simply binary, a probability would be better to represent their relationships. Second, the relationship between BEs and IEs often relies on the expert judgments, and this will include subjective factors and it would be reasonable to use a probability to describe their relationships. Therefore, the Noisy-OR gate Bayesian network, which is able to overcome the abovementioned problems (Feng et al., 2020), is introduced in this paper to derive the occurrence probability of navigational accidents, and it can be achieved in three steps.

(1) Transform the structure of FTA to qualitative part of BN. This process is simple and it can be easily transformed, the basic event is treated as root node, IE is treated as intermediate node and TE is treated as top node. After transformation, the graphical structure of the developed BN is shown in Figure 3.

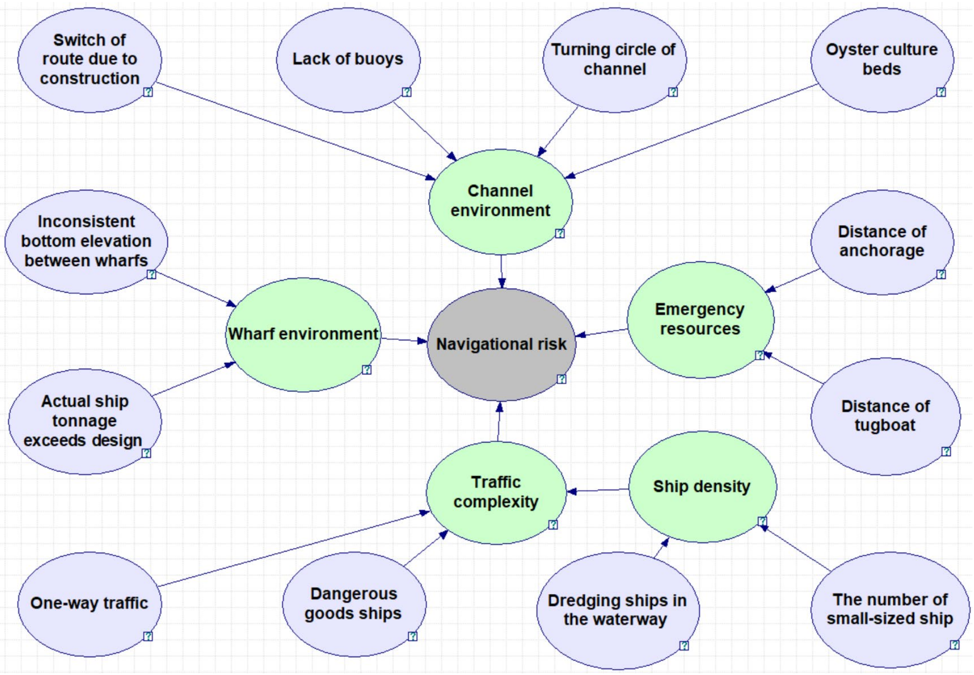

Figure 3 Graphical structure of the developed BN

(2) Derive the CPTs using Noisy-OR gate. The Noisy-or Gate model is often used to describe the internal relationship between several parent nodes and their associated child node. The parent nodes and child nodes only have two states, and the Noisy-OR gate BN should satisfy two conditions.

First, all variables should be independent from each other.

Second, if only the variable X_i occurs and the other variables do not occur, the other items X_P in the CPT of child node Y can be calculated using Eq. (9).

$$P(Y/X_p) = 1 - \prod_{i:x_i \in x_p} (1 - P_i) \tag{9}$$

Note that if Xp is an empty set, $P(Y/X_p) = 0$, which means that the node Y does not relies on the parent node Xp. This is the problem of traditional FTA, and in practice, the parent nodes should be leaky relationship with the child node, and it is denoted by X_L.

Specifically, suppose the node Y has only two parent nodes, which are represented by C_i and C_{all}. C_{all} is the sum of the factors other than C_i, the corresponding probabilities are defined by P_i and P_{all}, respectively (Peng et al., 2016), and the relationship can be derived in Eqs (10)-(11).

$$P(Y/C_{\mathrm{i}}) = 1 - (1 - P_i)(1 - P_{all}) = P_i + P_{all} - P_i P_{all} \tag{10}$$

$$P(Y/\overline{C}) = P_{all} \tag{11}$$

Afterwards, the Eq. (12) can be deduced as follows.

$$P_i = \frac{P(Y/C_{\mathrm{i}}) - P(Y/\overline{C})}{1 - P(Y/\overline{C})} \tag{12}$$

If there is a leaky node X_L, the conditional probability of node Y can be defined as Eq. (13).

$$P_i(Y) = 1 - (1 - P_i) \prod_{i:X_i \in X_P} (1 - P_i) \tag{13}$$

(3) Estimate the occurrence probability of navigational accidents. After defining the conditional probability of node Y with leaky node X_L, the CPTs of all the parent nodes can be obtained. Similar with the traditional BN, and the final occurrence probability of the navigational accidents can then be easily derived.

3 Application of the Noisy-OR gate BN model to the Qinzhou Port

3.1 Description of the Qinzhou Port

Qinzhou Port is located in the southern part of China, and it is the largest port in Guangxi. Moreover, it is also the fastest growing port in terms of the freight throughput. In 2019, the freight throughput is around 120 million tons, and there are around 2,911 ships leaving or arriving the Qinzhou Port each month. Owing to the fast development of this port, the maritime safety of this port becomes a significant issue. First, the ship density is high in the approach channel, owing to the fast development of the port, the ship density also grows, which increases the probability of maritime accidents. Second, owing to the strategy of "new western land-sea corridor", many infrastructures are constructing in the Qinzhou Port, there are 80 dredging vessels, which will definitely have a high impact on the maritime safety. Third, although the parameters of the wharfs are all designed and developed according to the regulations, the adjacent wharfs may have different bottom evaluation, which may cause the grounding accident if the large-sized ship sails in the adjacent wharf with low bottom evaluation accidentally. Fourth, there are many oyster culture beds in the Qinzhou Port, which has also caused collision accident in the past years.

According to the location of the different navigational environment of the wharfs and channels, the Qinzhou Port can be divided into five regions, and they are indicated in Figure 4. Specifically, the first region is the Jingujiang area, where are many wharfs close to each other and the adjacent wharfs may have different bottom evaluation. The second region is Dalanping, where many small-sized ships have to transfer cargo to other terminals in Guangxi, moreover, the tonnage of some actual ships is larger than the designed tonnage. The third region is Dahuan, where the turning circle of the channel is lower than the standard. The fourth region is Sandun, where dangerous goods ships often navigate in the nearby waterways, which has a significant impact on the navigational risk. The fifth region is the approach channel, where there are some illegal oyster culture beds and dredging ships.

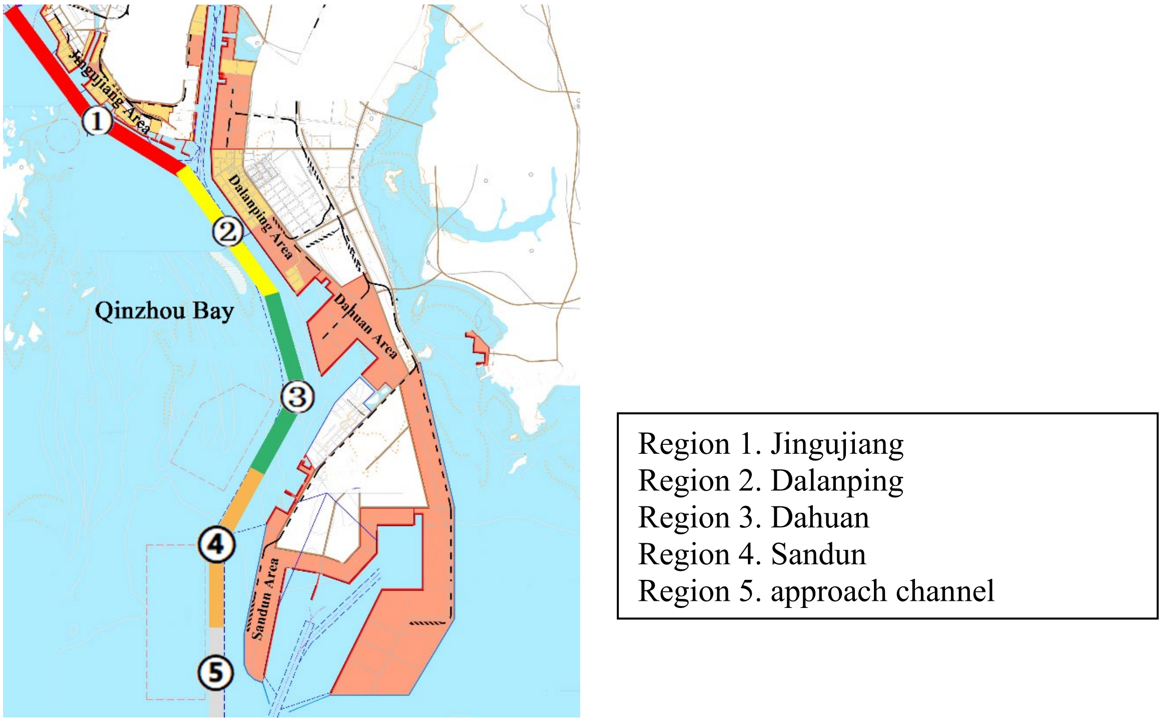

Figure 4 The five regions of the Qinzhou Port

3.2 Calculation of Bes probabilities for navigational risk based on fuzzy methods

Although some navigational accident data can be collected, it is hard to collect enough historical data to develop a data-driven model, the expert judgments, together with the data collected from the accident investigation reports, are used to estimate the occurrence probability of navigational accidents in this port. In this paper, only region 1 is used as an example to describe the modelling process in detail.

The linguistic variables, which is often used to facilitate the expert judgements (Wu et al., 2018; Pam et al., 2013), is introduced in this study. Similar with Pam et al. (2013), Five linguistic variables, Very Low (VL), Low (L), Average (A), High (H) and Very High (VH), are used in this paper. The corresponding numerical values are shown in Figure 5. In this study, a professor majoring risk analysis and two senior shipbuilders are invited to conduct the expert judgements.

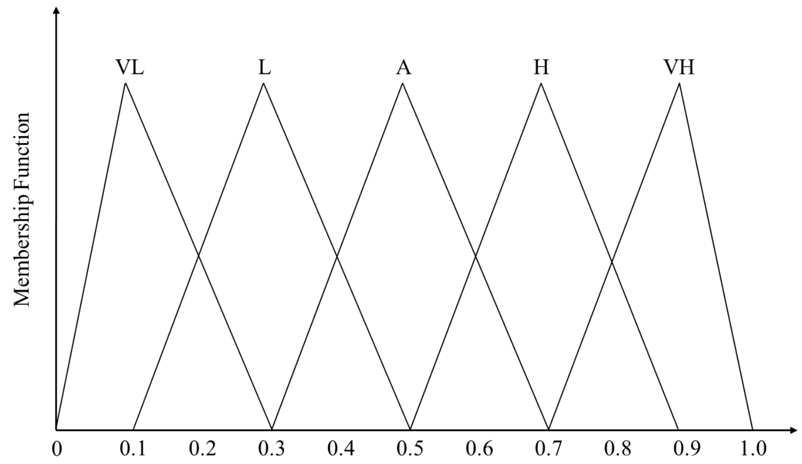

Figure 5 Corresponding numerical values for linguistic variables

The expert judgements of the 12 Bes are shown in Table 2. It can be seen that the three experts may have different expert judgments on some Bes (e.g. BE2), but also the same judgements on some specific Bes (e.g. BE8).

Table 2 Expert judgements on Bes using linguistic variables

Basic Event	Linguistic judgments of experts		
	Expert 1	Expert 2	Expert
BE1	L	L	VL
BE2	VL	L	A
BE3	L	VL	L
BE4	VL	L	VL
BE5	L	L	A
BE6	L	A	L
BE7	VL	L	L
BE8	L	L	L
BE9	L	VL	VL
BE10	VL	L	L
BE11	L	L	L
BE12	A	VL	L

Take BE2 as an example, the occurrence probability of each Bes can be derived. By introducing Eqs. (2)-(5), the similarity degree, expectancy evaluation, average agreement degree and relative agreement degree can be obtained, and the results are shown in Table 3. Moreover, the fuzzy number of BE6 can be derived after integration of three expert judgement, and the fuzzy possibility can be obtained after defuzzification using Eq. (6). Afterwards, the final occurrence probability can be estimated using Eq. (7).

Table 3 The occurrence probability calculation for BE2

Expert	E1	VL (0.0,0.1,0.3)	Expectancy evaluation	EV1	0.125
	E2	L (0.1,0.3,0.5)		EV2	0.300

	E3	A (0.3,0.5,0.7)		EV3	0.500
Similarity degree	S11	1.000	Average agreement degree	A(E1)	0.333
	S12	0.417		A(E2)	0.508
	S13	0.250		A(E3)	0.425
	S21	0.417	Relative agreement degree	RAD1	0.263
	S22	1.000		RAD2	0.401
	S23	0.600		RAD3	0.336
	S31	0.250			
	S32	0.600			
	S33	1.000			
BE6		(0.141,0.315,0.515)			
Defuzzification		0.323			
Occurrence probability		0.025			

Similar with the calculation process of BE2, the occurrence probability of each Bes in the five regions can be easily calculated, and the results are shown in Table 4. The results are reasonable owing to the following reasons: The occurrence probability of BE1 in Region 5 is higher than other regions owing to there are some illegal oyster culture beds close to the approach channel. The occurrence probability of BE2 in Region 3 is higher than others because of the turning circle of the channel is relatively small. The occurrence probabilities of BE3 in Region 1 and 2 are higher than others because there are a 1000 m and 4000 m long channel lack of buoy, respectively. The occurrence probabilities of BE4 in Region 4 and Region 5 are much higher than others because of the construction of new western land-sea corridor. The occurrence probability of BE5 in Region 1 is much higher than others because there are many wharfs with inconsistent bottom evaluation. The occurrence probability of BE6 in Region 1 and 2 are much higher than others because the actual ship tonnage is higher than the designed ship tonnage. The occurrence probability of BE7 is relatively low in all the five regions because the one-way traffic often lasts for a short time. The occurrence probability of BE8 is high in Region 4 because it is close to the 300,000-ton crude oil terminal, while in Region 3 there is also some dangerous goods terminals. The occurrence probability of BE9 in Region 5 is much higher than others because there are some dredging ships working in the approach channel, which has a significant impact on the navigation safety. The occurrence probability of BE10 in Region 2 and 3 are relatively high because there are many small-sized ships for transforming cargos to the other ports in Guangxi. The occurrence probability of BE11 in Region 2 is relatively high as the tugboats are far from these two regions. The occurrence probability of BE12 in Region 1 is high because this region is far from the anchorage.

Table 4 Occurrence probability of the BEs in each region

Basic Event	Region 1	Region 2	Region 3	Region 4	Region 5
BE1	0.693%	0.066%	0.019%	0.019%	1.623%
BE2	2.479%	0.019%	4.015%	2.479%	0.019%

BE3	0.693%	0.693%	0.066%	0.066%	0.019%
BE4	0.019%	0.066%	0.019%	1.623%	1.623%
BE5	4.015%	2.479%	0.693%	0.693%	0.066%
BE6	4.015%	4.015%	0.693%	0.066%	0.019%
BE7	0.693%	1.623%	0.019%	0.019%	0.019%
BE8	1.623%	0.693%	2.479%	4.015%	1.623%
BE9	0.019%	0.019%	1.623%	2.479%	4.015%
BE10	0.693%	2.479%	2.479%	0.693%	0.066%
BE11	1.623%	2.479%	0.693%	0.019%	0.066%
BE12	2.479%	0.693%	0.693%	0.066%	0.019%

3.3 Derivation of the CPTs using Noisy-OR gate BN

When transforming the FTA to BN, the conditional probability will be binary, which is absolute to describe the occurrence probability of the navigational accidents. In practice, the occurrence of navigational accidents should be a probability. Therefore, the Noisy-OR gate is introduced to derive the CPTs. Take the IE6 (i.e. ship density) as an example, the detailed derivation of the CPTs is described as follows.

As there are two child nodes (i.e. BE9 and BE10) for the IE6, if the relationships among these three factors are directly transformed from FTA to BN, the CPT will be binary and is shown in Table 5.

Table 5 Conditional probability table of IE6 using traditional method

BE9	Yes		No	
BE10	Many	Few	Many	Few
High	1	0	1	0
Low	0	1	0	1

From Table 2, it can be seen that the binary probability cannot accurately describe relationships. From example, if there are some dredging ships working in the channel and there are few small-sized ships, the ship density should not be 100% low. In order to address this problem, the Noisy-OR gate model is introduced and the probabilities used in the Noisy-OR gate model is defined as follows.

$$P(\text{Dredging ships at work in the waterway }) =$$
$$P(\text{Ship density} = \text{High} \mid \text{Dredging ships at work in the waterway } = \text{Overnormal}) = 0.90$$
$$P(\text{Dredging ships in the waterway }) =$$
$$P(\text{Ship density} = \text{Low} \mid \text{Dredging ships in the waterway } = \text{Normal}) = 0.14$$
$$P(\text{The number of small-sized ships}) =$$
$$P(\text{Ship density} = \text{High} \mid \text{The number of small-sized ship} = \text{Overnormal}) = 0.94$$
$$P(\text{The number of small-sized ships}) =$$
$$P(\text{Ship density} = \text{Low} \mid \text{The number of small-sized ships} = \text{Normal}) = 0.18$$

After defining the abovementioned probabilities, the connection probabilities could be calculated by using Eq. (11), in which P_{CBE9} is 0.286 and P_{CBE10} is 0.667. The unknown factor obeys the Gaussian probability density with a confidence level of 99%. Therefore, the results of IE6 are shown in Table 6, and all the other probabilities in the CPT can be calculated using this method.

Table 6. Conditional probability table of IE9 using Noisy-OR gate

BE9	Yes		No	
BE10	Many	Few	Many	Few
High	0.7646	0.2931	0.6703	0.01
Low	0.2354	0.7069	0.3297	0.99

After introducing the Noisy-OR gate method, it can be seen that the results are more reasonable than using traditional method. Specifically, when there are some dredging ships working in the channel and there are few small-sized ships, the ship density is low with a probability of 0.54 and is high with a probability of 0.46. By introducing this Noisy-OR gate method, all the CPTs in this navigational risk assessment model for Qinzhou Port can be derived.

3.4 Result analysis of the navigational risk in the Qinzhou Port

After obtaining the prior probability in Subsection 3.2 and the CPTs in Subsection 3.3, the final navigational risk can be derived. Take Region 1 as an example, the occurrence probability of Region 1 0.0745, and the result is shown in Figure 6. The result is reasonable when comparing with the navigational risk in other waterways. Specifically, in the Yangtze River, the navigational risk is 0.0575 (Zhang et al., 2013), in European waters, the result is 0.0592 (Sakar et al., 2021b), in the US Coast, the result is 0.0529 (Rawson and Brito 2020). Therefore, the occurrence probability is reasonable since the result of navigational risk is similar with the other waterways.

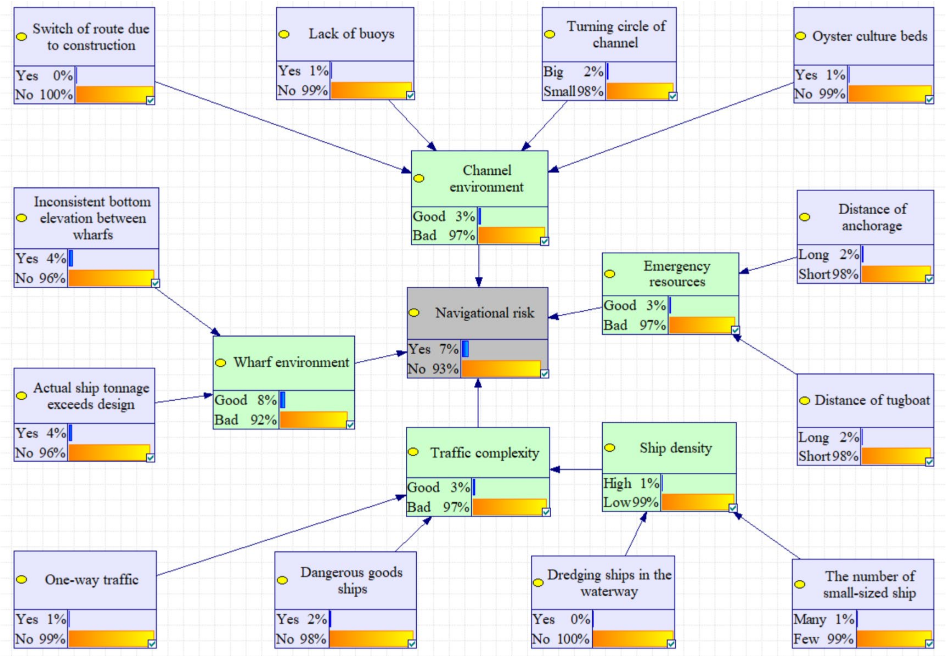

Figure 6 Occurrence probability estimation of Region 1 in Qinzhou Port

Similarly, the occurrence probability of navigational accidents can also be derived and the results are shown in Table 7.

Table 7 Occurrence probability of navigational accidents in five regions

Region	Occurrence probability
Region 1	0.07453
Region 2	0.06441
Region 3	0.05182
Region 4	0.05196
Region 5	0.04224

It can be seen that the highest occurrence likelihood is Region 1 while Region 5 is the lowest. This is because the prior probability in Region 1 is relatively high, including BE5 (4.015%), BE2 (2.479%), BE12 (2.479%), BE8 (1.623%) and BE11 (1.623%). Note that in Region 5, there are only one probability is high and other probabilities are the lowest including BE2 (0.019%), BE3 (0.019%), BE6 (0.019%), BE7 (0.019%) and BE12 (0.019%).

3.5 Minimum cut set to identify the key influencing factors

Compared with the traditional FTA and BN models, one significant merit of the Noisy-OR gate is that it can use Minimum cut set to identify the key influencing factors, this is very important because there are many influencing factors, but only some key influencing factors may cause the high risk of navigational accidents.

In the developed Noisy-OR gate BN model, the failure probability of the navigation risk is set to 1.0, indicating that a navigational accident already occurred. The strength of the influence of basic events can be judged by the thickness of the lines, and the thick lines represent the key influencing factors. Figure 7 shows the results, and where several of the thick lines constructing connected paths. Figure 8 demonstrates that 12 root nodes could influence the navigational accidents, but they only had four connections: BE5→IE2→TE and BE6→IE2→TE. The results can be used for the safety management of ship navigation in the Qinzhou Port.

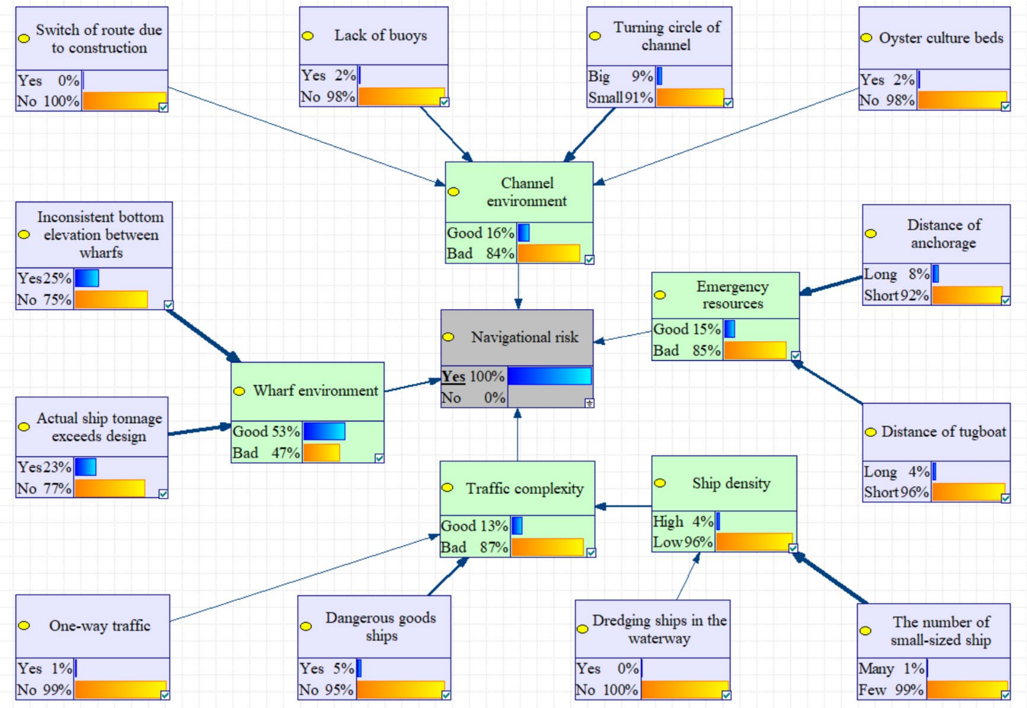

Figure 7 Key influencing factors identification using Noisy-OR gate BN

Similarly, the key influencing factors for the other regions can also be detected using the same method, and the results are shown in Table 8.

Table 8 The key influencing factors for the five regions

Region	Minimum cut sets
Region 1	BE5→IE2→TE, BE6→IE2→TE
Region 2	BE6→IE2→TE, BE10→IE6→IE4→TE
Region 3	BE2→IE1→TE, BE10→IE6→IE4→TE
Region 4	BE8→IE3→TE, BE9→IE6→IE4→TE
Region 5	BE4→IE1→TE, BE9→IE6→IE4→TE

3.6 Sensitivity analysis to quantify the sensitive influencing factors

Sensitivity analysis is often introduced to determine the degree of influence of the input parent node on the child output node (Shabarchin and Tesfamariam 2016). The top event failure probability (i.e. navigational risk) is treated as the target, sensitivity analysis can be carried out by changing the occurrence probability of navigational accidents. The results of the sensitivity analysis are shown in Figure 8.

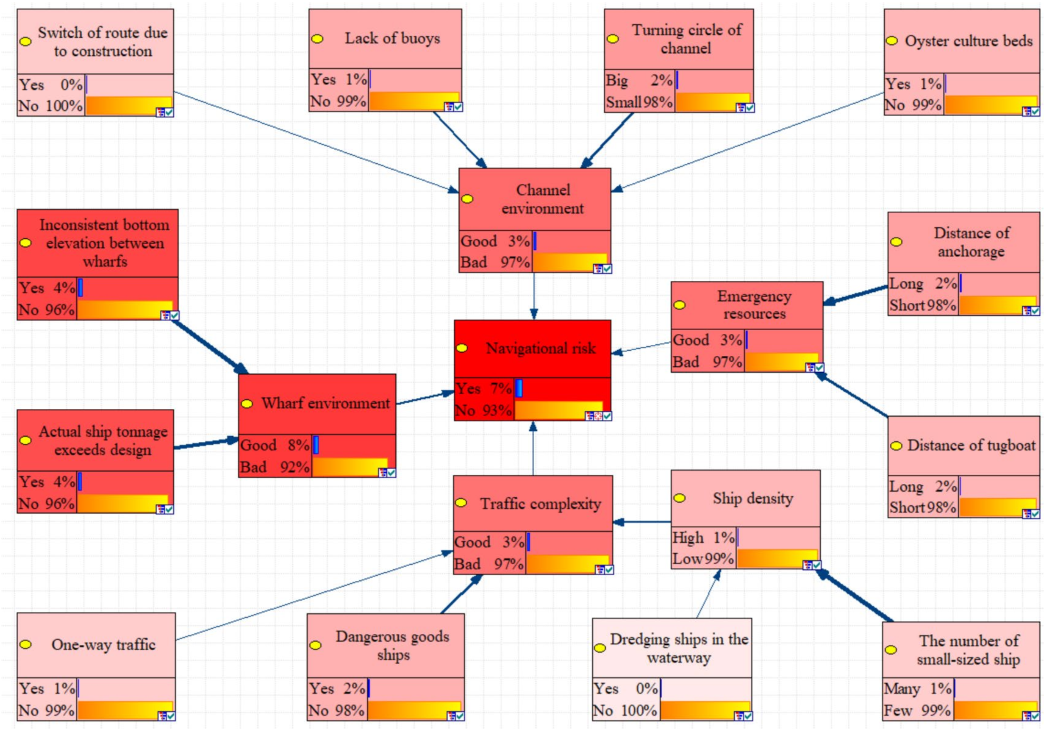

Figure 8 Sensitivity analysis of the navigational risk in the Qinzhou Port

Figure 8 shows that the sensitivity of the nodes could be divided into five levels. The first level includes wharf environment (IE2), Inconsistent bottom elevation between wharfs (BE5) and actual ship tonnage exceeds design (BE6). The second level includes channel environment (IE1), traffic complexity (IE3) and emergency resources (IE4). The third level includes turning circle of channel (BE2), dangerous goods ships (BE11), distance of tugboat (BE15) and distance of anchorage (BE16). The fourth level includes ship density (IE5), oyster culture beds (BE1), lack of buoys (BE3), one-way traffic (BE7) and the number of small-sized ships (BE10). The fifth level includes switch of route due to construction (BE4) and dredging ships in the waterway (BE9). The result of sensitivity analysis revealed that wharf environment (IE2), inconsistent bottom elevation between wharfs (BE5) and actual ship tonnage exceeds design (BE6) were the most influential factors for navigational risk.

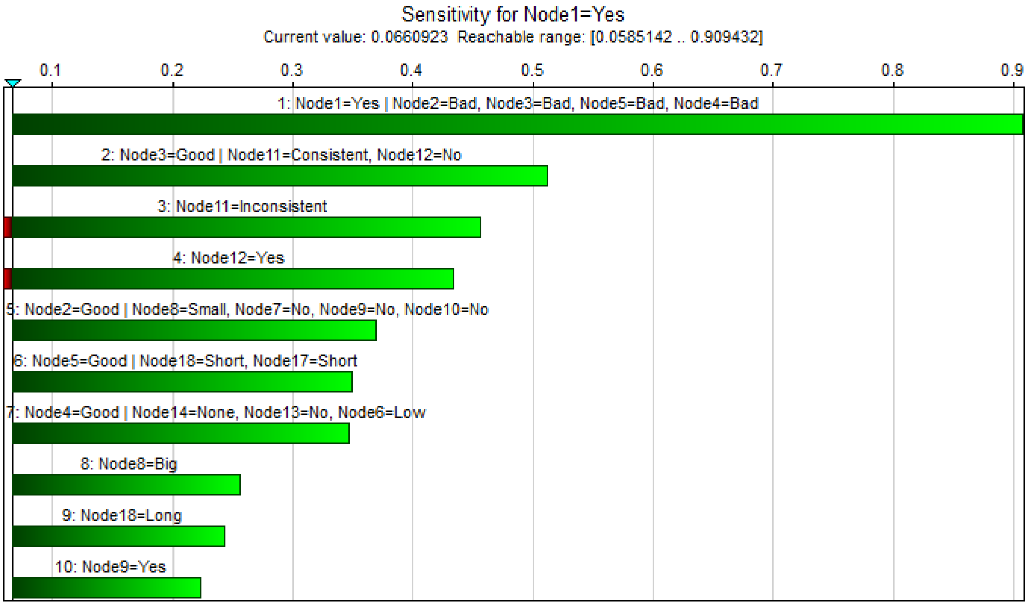

Figure 9 Tornado diagrams of the sensitivity analyses

Figure 9 show the tornado diagrams of the sensitivity analyses for navigational risk (TE) in the developed model. From further analysis, the most sensitive factors in Region 1 are wharf environment, inconsistent bottom elevation between wharfs, actual ship tonnage exceeds design, natural environment of channel, emergency resources, traffic complexity, turning circle of channel, distance of anchorage and lack of buoys. Moreover, the most basic sensitive nodes and the corresponding values in five regions are shown in Table 9.

Table 9 The most sensitive nodes and the corresponding values in five regions

Region	Most sensitive nodes	Corresponding values
Region 1	Inconsistent bottom elevation between wharfs (Node11), Actual ship tonnage exceeds design (Node12), Turning circle of channel (Node8), Distance of anchorage (Node18)	0.4573, 0.4354, 0.2571, 0.2448
Region 2	Actual ship tonnage exceeds design (Node12), Inconsistent bottom elevation between wharfs (Node11), One-way traffic (Node13), The number of small-sized ship BE10(Node16)	0.3980, 0.3128, 0.2738, 0.2506
Region 3	Turning circle of channel (Node8), Dangerous goods ships (Node14), Actual ship tonnage exceeds design (Node12), The number of small-sized ship (Node16)	0.3578, 0.3030, 0.2419, 0.2228
Region 4	Dangerous goods ships (Node14), Switch of route due to construction (Node10), Turning circle of channel (Node8), Dredging ships in the waterway (Node15)	0.3878, 0.2560, 0.2384, 0.2163
Region 5	Dredging ships in the waterway (Node15), Dangerous goods ships (Node14), Switch of route due to construction (Node10), Oyster culture beds (Node7)	0.2781, 0.2558, 0.2027, 0.2007

4 Conclusions

The main contribution of this paper is to construct a fuzzy fault tree analysis and Noisy OR gate Bayesian network model for the risk assessment of Qinzhou Port. The proposed model can overcome the problem of absolute descriptions of the conditional probabilities when transforming the fault tree to BN. Specifically, the fault tree is established using accident investigation reports, fuzzy set is used to derive the prior probability and Noisy OR gate BN is introduced to obtain the conditional probability tables. From further analysis, the key influencing factors and sensitive factors can also be identified in this developed model.

The results are compared with the Yangtze River, European waters, and the coast of the United States. From this comparison, it can be seen that the results are reasonable for assessing the occurrence likelihood for navigational accidents, which indicates that the proposed model is useful for assessing the occurrence likelihood for navigational accidents. Although this paper takes Qinzhou port as an example, the proposed model can also be applied to other waterways to predict the probability of maritime accidents if the proposed waterway data have similar characteristics.

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