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Use of Fuzzy Fault Tree Analysis and Noisy-OR Gate Bayesian Network for Navigational Risk Assessment in Qingzhou Port

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ABSTRACT: Collisions and groundings account for more than 80% among all types of maritime accidents, and risk assessment is an essential step in the formal safety assessment. This paper proposes a method based on fuzzy fault tree analysis and Noisy-OR gate Bayesian network for navigational risk assessment. First, a fault tree model was established with historical data, and the probability of basic events is calculated using fuzzy sets. Then, the Noisy-OR gate is utilized to determine the conditional probability of related nodes and obtain the probability distribution of the consequences in the Bayesian network. Finally, this proposed method is applied to Qinzhou Port. From sensitivity analysis, several predominant influencing factors are identified, including navigational area, ship type and time of the day. The results indicate that the consequence is sensitive to the position where the accidents occurred. Consequently, this paper provides a practical and reasonable method for risk assessment for navigational accidents.

1 INTRODUCTION

Collisions and groundings are the most frequent type of these maritime accidents, accounting for approximately 85% of maritime accidents [3, 14]. The navigational accident usually has serious consequences, such as loss of life, damage to property, pollution of waters etc. Therefore, it is essential to mitigate the navigational risk of maritime accidents [13, 17, 18].

Numerous approaches have been proposed for risk assessments [6]. [1] utilized the fuzzy bow-tie method to estimate the collision in STS operations, and analyzed the factors that have the strongest relationship with collision/contact accidents in STS operations. [15] proposed a mutual information-based Bayesian Network method for estimating the consequences of navigation accidents and identified the predominant factors of navigational accidents.

Bayesian networks (BN) are widely used for quantitative risk assessment due to their intuitive graphical structure and quantitative representation of the relationships between influencing factors [17, 18]. Moreover, it can also well handle the uncertainty. Owing to the above-mentioned advantages, it is used for the quantitative assessment of final risk. Moreover, as fuzzy fault trees can well describe the accident development using historical data, it is introduced to obtain basic events and associated failure probabilities.

2 DEVELOPMENT OF RISK ASSESSMENT MODEL

2.1 *Establishing a maritime accident risk assessment framework*

The proposed risk assessment framework for navigational accidents 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 based on historical data.

In the second step, the fault tree model is mapped into a Bayesian network and the conditional probabilities of the relevant nodes are determined using Noisy-OR gates.

The third step is to estimate occurrence probability of navigational accidents using Bayesian network. Regional factor analysis and sensitivity analysis are carried out in the developed Bayesian network.

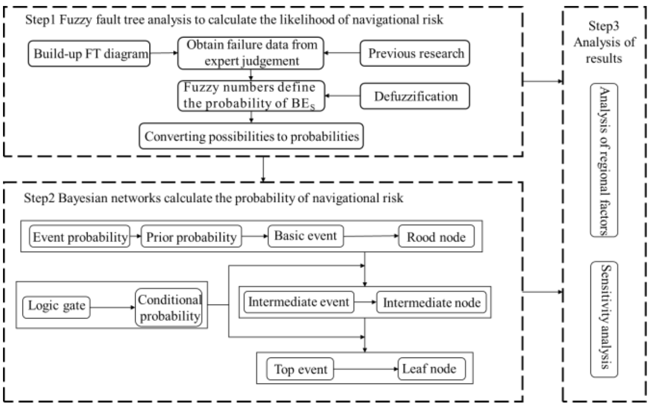

Figure 1. Risk assessment model framework for navigation

2.2 *Fuzzy fault tree analysis method*

2.2.1 *Construction of the fault tree*

Fault Tree Analysis (FTA) is often used to find the best way for risk mitigation. In a fault tree, top events, intermediate events and basic events are connected together by logic gates. The gates represent the relationships between the events [8].

In this paper, the navigational accident is considered as the top event (TE), and intermediate events are defined as crew, ship, waterway and emergency resource. The developed fault tree is shown in Figure.2. The proposed fault tree includes 23 BEs that contribute to the occurrence of the navigational accidents.

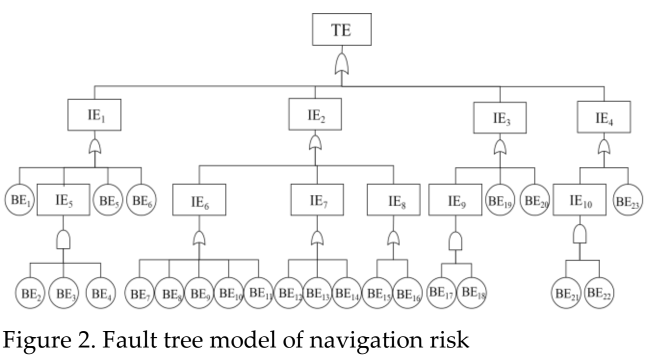

Figure 2. Fault tree model of navigation risk

2.2.2 *Identification of influencing factors for navigation accidents*

In order to identify the influencing factors, the historical data of maritime accidents in Qinzhou port are collected，which are 115 cases from 2018 to 2020. Moreover, previous studies are also used to facilitate the identification. The reasons for choosing the influencing factors are descried in detail as follows.

1. Top Event. The navigational risk is defined as top event, which is also the objective of this paper.
2. Intermediate Events. The intermediate events are often introduced to facilitate the modeling process. Traditionally, the influencing factors of navigational accidents can be categorized into four types, which are crew, waterway and emergency resource.
3. Basic Events. Crew includes lack of experience and training of crew, non-application of correct safety standards, etc, which are analyzed from the collected accident reports in the Qinzhou Port. Navigational environment includes the channel environment and wharf environment. Also communication between the ship and the marina is particularly important. Dangerous goods vessel is the most important factor in marine accidents, therefore, the setting of mobile safety zones and communication between dangerous goods vessels and other vessels 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.

To simplify events, the status of all nodes can be binary. In total, 23 BEs (basic events) and 10 IEs (intermediate events) were included in the FT (fault tree) diagram. Table 3 defines all potential failures related to collision/grounding during navigation.

2.3 *Using fuzzy fault tree methods to obtain BEs probability*

1. Fuzzy numbers to define probabilities of the BEs. The concept of fuzzy set theory was introduced by L.A. Zadeh [16] to deal with uncertain or vague information. A fuzzy set defined on a universe of discourse (U) is characterized by a membership function, $\mu(x)$, which takes values from the interval [0,1]. A membership function provides a measure of the degree of similarity of an element in U to the fuzzy subset. Fuzzy sets are defined for specific linguistic variables. Each linguistic term can be represented by a triangular, trapezoidal or Gaussian shape membership function. Here, triangular fuzzy numbers (TFNs) and trapezoidal fuzzy numbers (ZFNs) are employed on the strength of their simplicity and efficiency to quantify the probabilities of the BEs. The triangular representation shows the fuzzy possibility of a BE can be denoted by a triplet (a1,a2,a3) and the corresponding membership function is written as [12]:

$$\mu_{\tilde{A}}(\chi) = \begin{cases} 0 & ; \chi \le a_1 \\ (\chi - a_1)/(a_2 - a_1); & a_1 \le \chi \le a_2 \\ 0 & ; \chi \ge a_3 \end{cases} \tag{1}$$

A ZFN denoted by a quadruple (a1, a2, a3, a4) is defined as follows:

$$\mu_{\tilde{A}}(\chi)=\begin{cases} 0 & ; \chi \le a_1 \\ (\chi-a_1)/(a_2-a_1); & a_1 \le \chi \le a_2 \\ 1 & ; a_2 \le \chi \le a_3 \\ (a_4-\chi)/(a_4-a_3); & a_3 \le \chi \le a_4 \\ 0 & ; \chi \ge a_3 \end{cases} \quad (2)$$

2. Aggregation of fuzzy numbers of the BEs.
3. Defuzzification of the fuzzy BEs possibility.
4. Convert crisp possibility score (CPS) into probability value (PV) [11].
5. Navigational risk probability transformation.

The Fussell-Vesely Importance (FV-I) is employed to evaluate the contribution of each BE to the occurrence probability of the navigation accidents. This importance measure is sometimes called the top contribution importance. It provides a numerical significance of all the BEs in the developed fault tree for navigational risk assessment. The improved FV-I of a BE is calculated by the following equation [10]:

$$I_{x_i}^{FV}=\frac{(P_{TE}-P_{TE}^{x_i=0})\cdot P_{BE_i}}{P_{TE}} \quad (3)$$

where $I_{x_i}^{FV}$ is the FV-I index of *i-th* BE; $P_{TE}^{x_i=0}$ is the occurrence probability of the navigation risk by setting the probability of *i-th* BE to 0.

Then, the FV-I values are defined as probabilities for the BES of the Bayesian network to derive probability transformation values for regional navigational risk, and rank the degree of risk in each region by the probability transformation values for regional navigational risk.

2.4 *Noisy-OR gate Bayesian network*

2.4.1 *Mapping the fault tree model into BNs*

The fault tree model often uses logical "OR" and "AND" gates to express the relationships among various events. The mapping steps are presented in Figure. 3. In the established failure tree model, there were 23 basic events mapped into 23 root nodes, 10 intermediate events mapped into 10 intermediate nodes, and the top event mapped into the leaf node. Figure. 4 displays the BN of the navigation risk assessment system in GeNIe-Academic software.

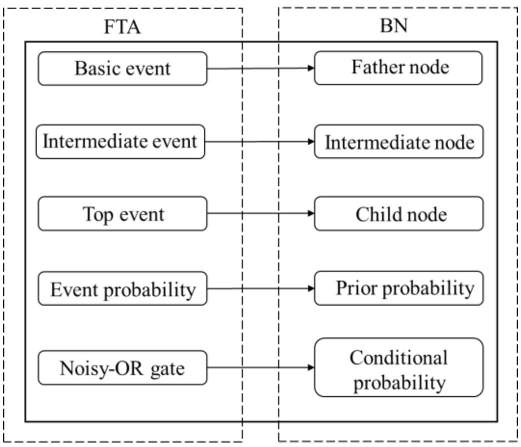

Figure 3. Relationship between FTA and the BN

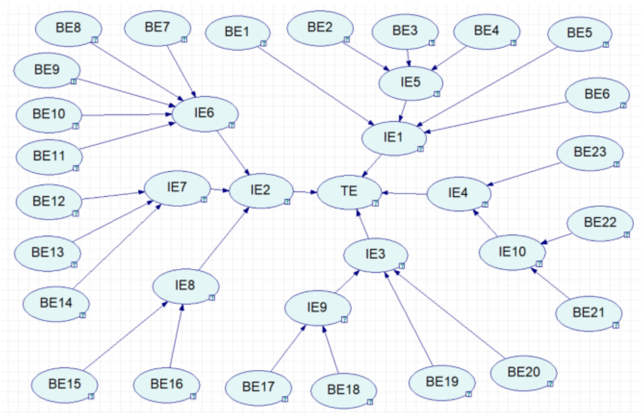

Figure 4. Bayesian network of navigation risk

2.4.2 *Noisy-OR gate model*

The Noisy-OR gate model is used to describe the relationships between influencing variables and their associated child nodes Y. Each variable has only two states, and the Bayesian model based on the Noisy-OR gate must satisfy two conditions [5]:

1. All variables are independent of each other;
2. Assuming that one of the variables x_i occurs and other variables do not occur, the occurrence of its child node Y can be expressed as $P_i=P(Y=1|x_1,x_2,\cdots,x_i,x_{i+1},\cdots,x_n)$, and then the other terms X_p in the CPT of child node Y determined by $P_1,P_2,\cdots,P_i,\cdots,P_n$ can be expressed as Eq. (4) follows:

$$P(Y/X_p)=1-\prod_{i:x_i\in x_p}(1-P_i) \quad (4)$$

1 if Xp is an empty set, then $P(Y/X_p)=0$, indicating that the probability of node Y has no relationship with parent node Xp. This does not match with the actual situation, therefore, all influencing factors affecting node Y are defined as Leaky nodes, represented by XL. Next, the model can be redefined as the Leaky Noisy-OR gate model.

The mathematical model is derived as follows: Suppose that child node Y has only two parent nodes, which are represented by C_i and C_{all}, respectively, where C_{all} represents the sum of the other factors except for C_i. Their corresponding probabilities are represented by Pi and Pall, respectively [7]. The detailed calculation process is shown in [4].

3 APPLICATION OF THE RISK ASSESSMENT METHOD ON THE QINGZHOU PORT

3.1 *Calculation of BEs probabilities for navigational risk based on fuzzy methods*

The port of Qinzhou was divided into five regions based on geographical features, as shown in Figure 5, and the developed model are applied to analyse navigational risk in those five regions. In this paper, only region 1 is used as an example to describe the modeling process.

Figure 5. Geographical location of the five regions in Qinzhou Port

Owing to a lack of historical data, the fuzzy set theory and experts' linguistic judgments are combined to quantify the probability of possible BEs occurrence. In this study, the assessment was performed by three experts, including a risk analyst and two senior shipwrights. The linguistic expressions of marine experts were converted into fuzzy numbers using the numerical approach method. Linguistic scales, illustrated in Table 1. We propose a 7-point scale {Very Low (VL), Low (L), moderate Low (ML), Medium (M), moderate High (MH), High (H) and Very High (VH)} through which experts will make linguistic judgments on the probability of BEs. Figure. 6 shows the number and membership functions of the fuzzy sets that were developed [2]. To facilitate the analysis, we converted the TFNs of the BE probabilities into the corresponding ZFNs; for example, TFN (a1, a2, a3) can be expressed as ZFN (a1, a2, a2, a3). The results of the expert assessment of each BES are shown in Table 2.

Table 1. Linguistic terms and trapezoidal fuzzy numbers of possibilities

Linguistic term	Fuzzy numbers
Very low (VL)	(0.0,0.0,0.1,0.2)
Low (L)	(0.1,0.2,0.2,0.3)
Medium low (ML)	(0.2,0.3,0.4,0.5)
Medium (M)	(0.4,0.5,0.5,0.6)
Medium high (MH)	(0.5,0.6,0.7,0.8)
High (H)	(0.7,0.8,0.8,0.9)
Very high (VH)	(0.8,0.9,1.0,1.0)

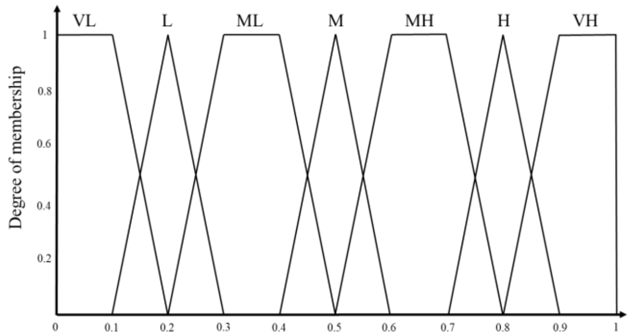

Figure 6. Fuzzy number

3.2 *Mapping the fault tree model into BNs*

The conditional probability in the traditional Bayesian network uses 100% to describe the occurrence probability, in practice, it should be a probability. Therefore, the Noisy-OR gate model, which can overcome this problem, is introduced. Take the Engineering facilities (IE8) as an example, two root nodes (BE15 and BE16) can be used to construct the Noisy-OR gate model.

Table 2. Fuzzy possibility values for BEs in fuzzy navigation risk FTA

Basic Event	Failure descriptions	Linguistic judgments of experts Expert 1	Expert 2	Expert 3	Aggregation of fuzzy numbers
BE1	Lack of experience and training	L	ML	M	(0.168,0.268,0.335,0.435)
BE2	Safe speed not used	ML	M	ML	(0.240,0.340,0.373,0.473)
BE3	Unauthorized changes to voyage plans by ships	MH	ML	M	(0.267,0.367,0.434,0.533)
BE4	Failure to strictly enforce safe operating standards for ship navigation	ML	MH	ML	(0.264,0.364,0.432,0.532)
BE5	Poor judgement and inappropriate measures	M	MH	M	(0.333,0.133,0.466,0.566)
BE6	Solidified operation, slow to react in the face of unexpected events	ML	L	ML	(0.241,0.341,0.376,0.476)
BE7	Waterway oyster barrier	VL	L	L	(0.062,0.124,0.162,0.262)
BE8	The waterway is a single side marker	VL	L	ML	(0.100,0.168,0.232,0.332)
BE9	Lack of marker buoys in dangerous shallows	L	L	VL	(0.074,0.149,0.174,0.274)
BE10	Small turning radius	L	VL	L	(0.073,0.146,0.173,0.273)
BE11	Bend improvement section form shallow area	VL	VL	VL	(0.000,0.000,0.100,0.200)
BE12	Lack of effective communication between the ship and the terminal	ML	L	ML	(0.170,0.270,0.341,0.441)
BE13	Inconsistent floor elevation between docks	VL	VL	VL	(0.000,0.000,0.100,0.200)
BE14	Mismatch between berthing tonnage and the actual quay	L	VL	L	(0.073,0.147,0.173,0.273)
BE15	Construction vessels occupying waterways	MH	H	MH	(0.466,0.566,0.632,0.732)
BE16	Construction Closure	M	MH	M	(0.340,0.440,0.470,0.570)
BE17	Mobile safety zone setup	ML	L	ML	(0.170,0.270,0.341,0.341)
BE18	Communication between dangerous goods vessels and other vessels	L	L	ML	(0.128,0.228,0.257,0.357)
BE19	Shuttle buses increase the density of traffic flow	MH	M	ML	(0.264,0.364,0.432,0.532)
BE20	Construction vessels increase the density of traffic flow	H	H	MH	(0.429,0.529,0.558,0.658)
BE21	Lack of tugboat towing	ML	M	ML	(0.170,0.270,0.341,0.441)
BE22	Lack of emergency anchorage	M	L	L	(0.132,0.232,0.264,0.364)
BE23	Insufficient sensitivity to accident and risk information	ML	VL	L	(0.107,0.179,0.243,0.343)

From Table 3, the probabilities can be defined as follows.

$P(BE_{15}) = P(IE_8 = 1 \mid BE_{15} = 1) = 0.92$,

$P(BE_{15}) = P(IE_8 = 0 \mid BE_{15} = 0) = 0.11$,

$P(BE_{16}) = P(IE_8 = 1 \mid BE_{16} = 1) = 0.91$,

$P(BE_{15}) = P(IE_8 = 1 \mid BE_{15} = 1) = 0.18$

The connected probability could be computed that P_{CBE15} is 0.272 and P_{CBE16} is 0.5. The unknown factor obeys the Gaussian probability density and its confidence level is 99%. Therefore, we can calculate x_i, the conditional probability distribution of IE8 (see Table 3).

Table 3. Conditional probability table of IE8

BE15	T		F	
BE16	T	F	T	F
T	0.63964	0.27928	0.505	0.01
F	0.36036	0.72072	0.495	0.99

Figure. 4 reveals that IE6, IE7, and IE8 also constructed a local network.

$P(IE_6) = P(IE_2 = 1 \mid IE_6 = 1) = 0.95$,

$P(IE_6) = P(IE_2 = 0 \mid IE_6 = 0) = 0.11$,

$P(IE_7) = P(IE_2 = 1 \mid IE_7 = 1) = 0.91$,

$P(IE_7) = P(IE_2 = 0 \mid IE_7 = 0) = 0.15$,

$P(IE_8) = P(IE_2 = 1 \mid IE_8 = 1) = 0.91$,

$P(IE_8) = P(IE_2 = 0 \mid IE_8 = 0) = 0.13$

Their connected probability can be computed that P_{CIE6} is 0.558, P_{CIE7} is 0.4, P_{CIE8} is 0.307, the CPT of IE2 can be obtained. Table 6 presents the conditional probability of IE2. The CPT of IE2 is more reasonable than conditional. All CPTs could be obtained by following these steps. The final calculated probability transformation value of heading risk for Area 1 is 0.05367. Figure. 7 displays the results based on the modified Noisy-OR gate.

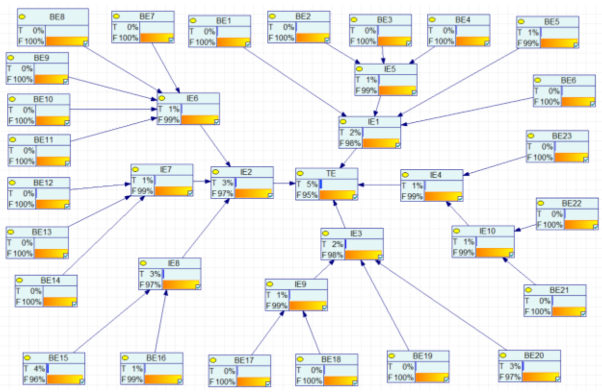

Figure 7. Failure probability based on the Noisy-OR gate

4 RESULT AND DISCUSSION

4.1 *Subsection*

In this study, the fault tree model shown in Figure. 3 was used to analyze the navigational risk. Besides, as the basic events can have a direct impact on the occurrence of the navigational risk, the relationship among various events are connected using logical OR gates.

In the Noisy-OR gate BN, if the accident has already occurred, the failure probability of the navigation risk was set 1.0. Figure. 8 shows the results of the BN, with the thick lines representing the predominant influential factors, and where several of the thick lines are used to construct connected paths for the probability of failure TE.

Figure. 8 reveals that 12 root nodes could influence the entire system, but they only had four connections: BE8→IE6→IE2→TE, BE10→IE6→IE2→TE, BE12→IE7→IE2→TE and BE14→IE7→IE2→TE. This analysis is used to discover the impact of influencing factors on the top event.

Table 6. Conditional probability table of IE2

BE6	T				F			
BE7	T		F		T		F	
BE8	T	F	T	F	T	F	T	F
T	0.8181	0.7375	0.6968	0.5624	0.5884	0.406	0.3139	0.01
F	0.1819	0.2625	0.3032	0.4376	0.4116	0.594	0.06861	0.99

Table 7. Comparison of different areas

Area	Failure probability transformation value	Minimum cut sets	Top 10 basic events
1	0.05367	BE8→IE6→IE2→TE, BE10→IE6→IE2→TE, BE12→IE7→IE2→TE, BE14→IE7→IE2→TE	BE20(node28), BE15(node24), IE4(node3), BE16(node25), IE8(node15), IE5(node8), BE5(node8), BE4(node12), IE3(node5)
2	0.07328	BE8→IE6→IE2→TE, BE10→IE6→IE2→TE, BE12→IE7→IE2→TE, BE14→IE7→IE2→TE	BE10(node19), IE1(node2), BE23(node31), BE18(node30), BE20(node28), IE9(node26), IE8(node15), BE16(node25), BE23(node31)
3	0.07911	BE8→IE6→IE2→TE, BE10→IE6→IE2→TE, BE12→IE7→IE2→TE, BE14→IE7→IE2→TE	BE10(node19), IE4 (node3), IE9(node26), BE18 (node30), BE20 (node28), BE14(node24), IE8 (node15), BE16 (node25), BE3(node10)
4	0.07259	BE8→IE6→IE2→TE, BE10→IE6→IE2→TE, BE12→IE7→IE2→TE, BE14→IE7→IE2→TE	BE10(node19), BE7(node16), BE17(node29), BE18(node30), BE14 (node23), IE4 (node3), BE12 (node21), BE9(node18), BE3(node10)
5	0.08901	BE8→IE6→IE2→TE, BE10→IE6→IE2→TE, BE12→IE7→IE2→TE, BE14→IE7→IE2→TE	IE6 (node13), BE14 (node23), IE2(node4), BE12(node21), BE18(node30), IE9(node26) BE10(node19), BE17(node29), IE4 (node3)

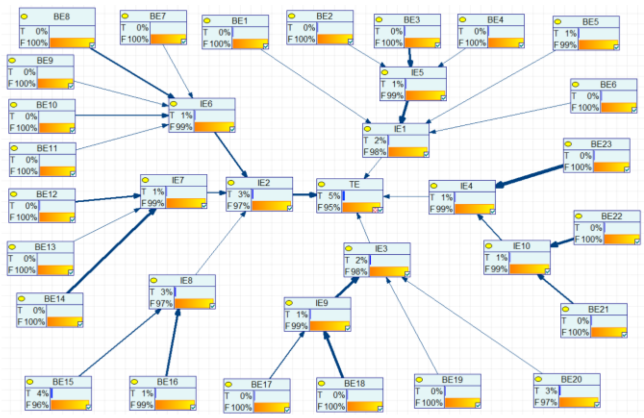

Figure 8. Risk diagnosis–based BN of Noisy-OR gates

4.2 *Sensitivity analysis*

Sensitivity analysis is used to discover the degree of influence caused by input leaf node on the root output nodes [9]. The failure probability of top event (TE) is set as the target, and the sensitivity analysis is carried out by changing the probability of top event. Figure. 9 shows the results of the sensitivity analysis.

Figure. 9 shows that the sensitivity of the nodes could be divided into five levels. The first level includes environmental (IE2) and waterway (IE6), the second level includes crew (IE1), ship (IE3), emergency resources (IE4), failure to implement correct safety standards (IE5), quayside (IE7) and insufficient sensitivity to accident and risk information (BE23). The third level includes engineering facilities (IE8), dangerous goods ship (IE9), lack of resources (IE10), lack of experience and training (BE1), unauthorized changes to voyage plans by ships (BE3), lack of effective communication between the ship and the terminal (BE12), construction closure (BE16) and communication between dangerous goods vessels and other vessels (BE18). The fourth level includes waterway oyster barrier (BE7), the waterway is a single side marker (BE8), lack of marker buoys in dangerous shallows (BE9), small turning radius (BE10), bend improvement section form shallow area (BE11), inconsistent floor elevation between docks (BE13), and mismatch between berthing tonnage and the actual quay (BE14). The remaining basic events are in the fifth level. The result of sensitivity analysis revealed that environmental (IE2) and waterway (IE6) were the most influential factors for navigational risk.

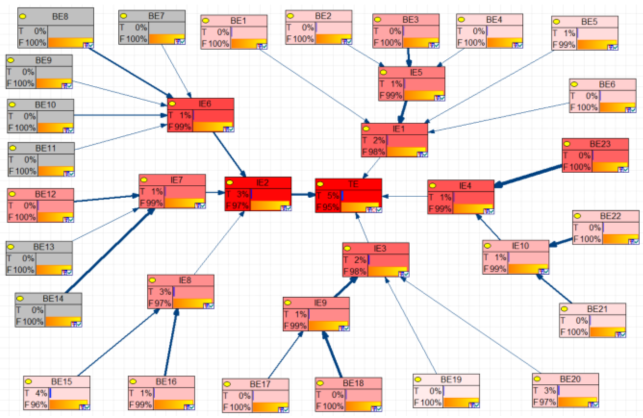

Figure 9. Sensitivity analysis of the BN

Figure 10 show the tornado diagrams of the sensitivity analyses for failure probability (TE) in the developed model. Also the most sensitive events were BE20 (node28), BE15 (node24), IE4 (node3), BE16 (node25), IE8 (node15), IE5 (node8), BE5 (node8), BE4 (node12) and IE3 (node5), among these factors, in Area 1, BE20, BE15, BE16, BE5, BE4 have a greater impact on the navigational risk than other factors.

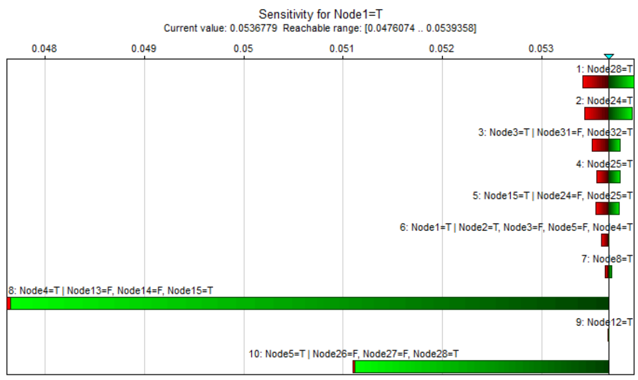

Figure 10. Sensitive analysis of top 10 basic event

4.3 *Comparative regional extent*

After risk assessment of the five regions of Qinzhou Port, the probability of navigation risk, minimum cut set, and the ten basic items for each region are shown in Table7. It can be seen that Area 1 is a lower-risk area, Area 2 and Area 4 are low-risk areas, Area 3 is a medium-risk area, and Area 5 is a high-risk area, the results show that occurrence probability has a geographical character. Also, the CPTs derived using the same Noisy-OR gate for the five regions have the same minimum cut set, indicating that the minimum cut set is related to the Noisy-OR gate, but there are large differences in the top ten basic events derived from the tornado plots using sensitivity analysis.

5 CONCLUSIONS

The main contribution of this paper is to propose the fuzzy fault tree analysis, Noisy-OR gate Bayesian network method for estimating the level of risk in navigation accident areas and identification of the main factors in such accidents. First, the influencing factors that contribute to the risk of navigational accidents were identified from the historical data and previous research and used as the basic events to construct a navigational risk fault tree. Second, fuzzy sets were utilized to obtain the probability of each basic event and to map the fault tree to a BN, the graphical structure of the BN could then be derived. Finally, CPTs were established using historical data and Noisy-OR gate. By applying this method, the occurrence probability can be obtained by using fuzzy fault trees and Noisy-OR gate Bayesian networks. The main influencing factors of navigation risk can be derived. Based on these findings, countermeasures can be taken to reduce the occurrence probability of such accidents.

Although this paper uses the Qinzhou port as a case study, the proposed model could be also applied to other waterways to predict the occurrence probability of maritime accidents if the data of the proposed waterways have similar characteristics.

ACKNOWLEDGEMENTS

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