

An Expert Elicitation Analysis for Vessel Allision Risk Near the Offshore Wind Farm by Using Fuzzy Rule-Based Bayesian Network

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ABSTRACT: This paper develops an expert based framework for analysing and synthesising the ship allision risk near the offshore wind farm (OWF) on the basis of a generic Fuzzy Bayesian network and FMEA analysis. This framework is specifically intended to overcome the difficulty of using traditional risk assessment methods in OWF allision. Under the introduced framework, subjective belief degrees are assigned to model the incompleteness encountered in establishing the knowledge base. The fuzzy transformation technology is then used to introduce all judgements results under various situations. Fully, a Bayesian network is established to aggregate all relevant attributes to the conclusion and to prioritise potential allision risk level of each ship categories. A series of case studies of different ship categories are studied to illustrate the application of the proposed framework. Results show that the fishing vessel and the service vessel have a higher allision risk than the merchant vessel due to insufficient risk detection. The collision consequence of the tanker is significantly higher than other types of vessel. The framework facilitates subjective risk assessment when historical failure data is not available in their practice, which provides support to OWF-safeguarding and decision-making.

1 INTRODUCTION

Wind energy is an environment-friendly and sustainable energy. To develop this burgeoning industry for electrical generation, many countries have developed large numbers of offshore wind farms (OWFs) near the coastal area. As a type of human installation, the OWF leads to a potential collision risk when vessels are passing the OWF area, it is the main issue amongst the OWF impacts to navigation [1]. Current research works have presented a general understanding knowledge of OWF impacts to navigation. For example, several studies used the vessel Automatic Identification System database to assess OWFs influence on the vessel traffic in the Thames Estuary, the Penghu waterway and the south coast of Busan [2][3][4]. According to past research works of vessel traffic flow

studies, vessels under different categories may conduct different collision probabilities [5][6][7]. Although there are several issues have been discussed amount these research works, the lack of a conceptual framework of evaluating the ship allision risk, the discussion about OWF impacts on collision probabilities under different ship categories and discussion of the consequence of ship allision are too general. These drawbacks were raised when applying traditional risk analyses in OWF safety study due to following reasons, the accident records for vessel collided with OWF turbines are rare and hard to acquire; understanding of allision mechanism of OWFs still uncompleted [8]. Therefore, this paper introduces a Bayesian Network (BN) model to analyse the vessel collision risk near the OWF area. On the basis of the failure mode and effects analysis (FMEA), the BN model is established to provide a general risk

analysis framework. An expert-based consulting board is constructed to judge the vessel allision risk under different categories based on expert's knowledge. To improve the accuracy of transforming the belief degree assignments of the vessel allision risk in the vicinity of the OWF. A fuzzy transforming technology is used to transform the expert judgement of each attendance attribute into the conditional probabilities to link the risk factors. The developed BN model is then implemented to prioritise the vessel allision risk under different categories, which extend the understanding of the OWF impacts to navigation environment.

The paper is presented as follows: Section 2 introduces the methodology of developing a hybrid risk model based on FMEA. In section 3, the proposed model is implemented to deal with a subjective database to evaluate the allision risk of different vessel categories. Section 4 gives a discussion of the study result and conclusion from this study is drawn in Section 5.

2 METHODOLOGY

In this section, a rule-based BN model on the basis of the FMEA is introduced. The FMEA is one of the earliest risk analysis method, it was widely used in dealing with the potential risks that conduct mechanical failures or engineering accidents [9]–[11]. The risk structure of FMEA consists with three factors that include the probability of accident occurred (L), the consequence severity of the accident (C) and the likelihood ranking of potential risks are detected before it happens (P). The kernel of this approach is to introduce reliable database and transform the database into the conclusion by using the risk priority number (RPN), then the L , C and P are aggregated to conclude the risk priority of the scenarios. [12][13]. However, when applying the method in the OWF area, the accuracy and the reliability of the FMEA approach is limited due to the insufficient database both of accident records or judgements. Therefore, a fuzzy rule-based BN and a transforming framework are developed to help experts to provide more precise judgements and to transform the judgements into marginal probabilities [14]. Then the BN can be used to aggregate all risk factors into conclusion.

2.1 Fuzzy mapping and transforming

When applying the expert elicitation, experts may express their judgement in different ways. This requires a method to integrate the judgement results under various form into a consistent way before introducing to the risk analysis model [9]. We used the fuzzy mapping approach to normalise the expert judgement and to aggregate the data. On the basis of the FMEA approach, three risk factors of L , C and P are described using the linguistic variables associated with the antecedent attributes. Refer to the literature survey, the linguistic variables used to estimate L , C and P are defined as follows: the L is defined with five linguistic grades as (L_1 =very low, L_2 =low, L_3 =average,

L_4 =frequent and L_5 =very frequent); the C is defined as (C_1 =negligible, C_2 =marginal, C_3 =moderate, C_4 =critical and C_5 =catastrophic); the P is described as (P_1 =unlikely, P_2 =reasonable unlikely, L_3 =likely, L_4 =reasealable likely and L_5 =definite) [14]. To transform the expert judgement into the belief degree of linguistic terms, the fuzzy mapping function is used and the membership function of each linguistic variables is defined with an equal interval as $L_1=C_1=P_1=0.1$, $L_2=C_2=P_2=0.3$, $L_3=C_3=P_3=0.5$, $L_4=C_4=P_4=0.7$, $L_5=C_5=P_5=0.9$. Three examples of transforming the expert judgements under different forms are given as followings. For the shape of trapezoidal, antecedent attributes are given with the format of the lowest possible number lp , the lowest belief number lb , the highest belief number hb and the highest possible number hp , which as (lp , lb , hb , hp).

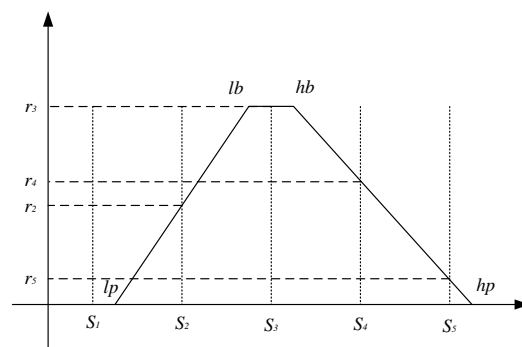


Figure 1. Fuzzy mapping for the shape of the trapezoidal format

The Figure 1 graphically shows the transforming function for the judgement $J = (lp=0.15, lb=0.45, hb=0.55, hp=0.95)$ gives by an expert. The J can be transformed into the fuzzy mapping distribution set D including each linguistic term S , and the $D = (S_1 = 0, S_2 = 0.5, S_3 = 1, S_4 = 0.625, S_5 = 0.125)$. Normalising the D , the belief degree distribution Q of each S is computed as $Q = (0 (S_1), 0.22 (S_2), 0.44 (S_3), 0.28 (S_4), 0.06 (S_5))$.

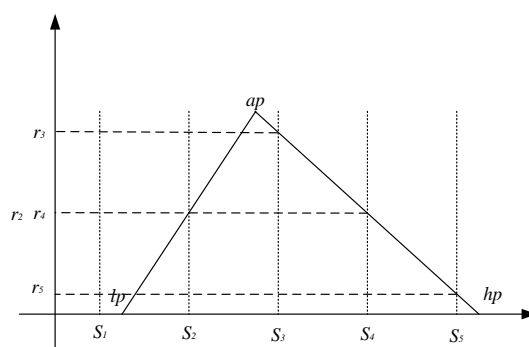


Figure 2 Fuzzy mapping for the shape of the triangular format

A judgement used the triangular format can be transformed as shown in Figure 2. The judgement expresses with three parameters: the lowest possible number lp , the average possible number ap and the highest possible number hp , show as (lp , ap , hp). Gives a $J = (lp=0.15, ap=0.45, hp=0.95)$, the D is calculated as ($S_1 = 0, S_2 = 0.5, S_3 = 0.9, S_4 = 0.5, S_5 = 0.1$) and then the $Q = (S_1 = 0, S_2 = 0.25, S_3 = 0.45, S_4 = 0.25, S_5 = 0.05)$

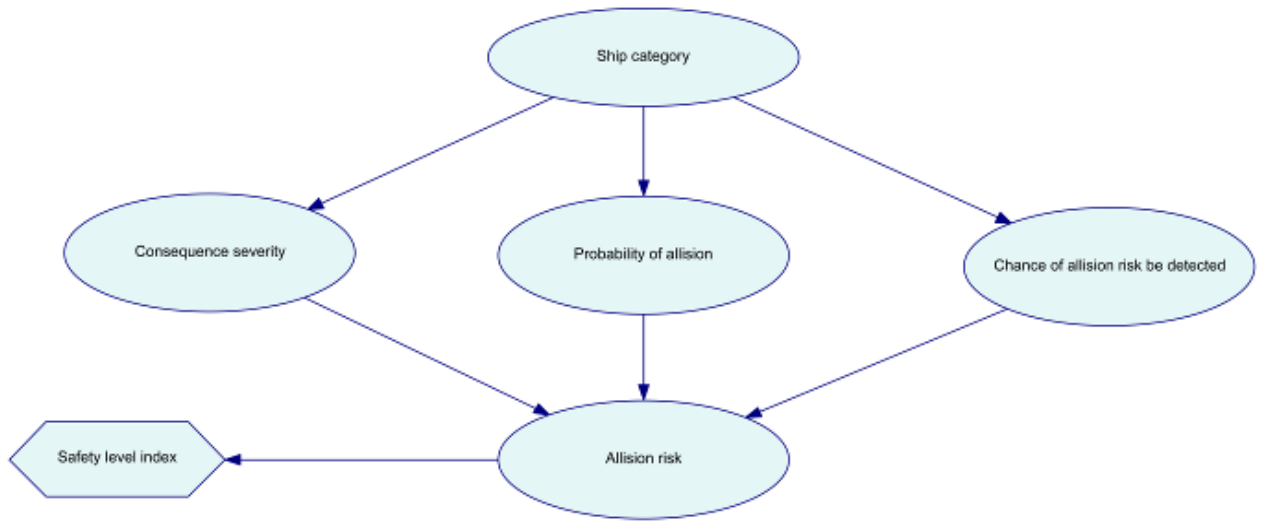


Figure 4 BN for the vessel allision risk in FMEA

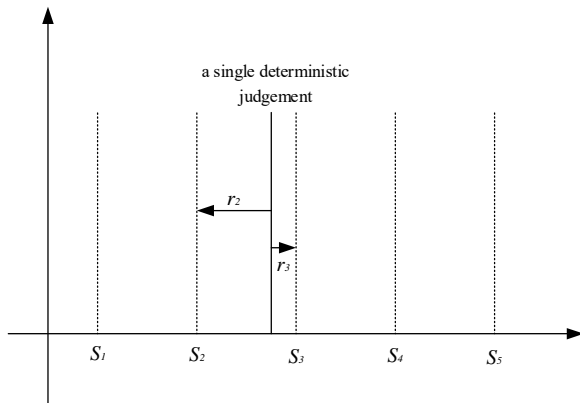


Figure 3. Fuzzy mapping for the shape of the single deterministic format

According to the fuzzy mapping function, a single deterministic judgement can be transformed according to the mean maximum method. It graphically as Figure 3: if $J = 0.45$, then $D = Q = (S_1 = 0, S_2 = 0.25, S_3 = 0.75, S_4 = 0, S_5 = 0)$.

2.2 Development of rule bases for Bayesian structures in FMEA

In the FMEA, the allision risk for vessel near the OWF is influenced by three factors as the probability of allision (L), consequence severity (C) and the chance of allision risk be detected (P). The FMEA based BN structure is shown in Figure 4.

To linked each node in the BN, the *IF-THEN* rule is used to develop the conditional probability table (CPT) between parent nodes of P , L and C with the final node of allision risk [14]. A set of belief rules BR_h consist of the *IF-THEN* rule with a belief structure that applying in FMEA can be expressed as:

BR_h : IF P_i and C_j and L_k , THEN $R^h = \{(\beta_1^h, R_1), (\beta_2^h, R_2), (\beta_3^h, R_3), (\beta_4^h, R_4), (\beta_5^h, R_5)\}$, where $(i, j, k = 1, 2, 3, 4, 5, h=1, 2, \dots, 125)$.

where β_n^h ($n = 1, 2, 3, 4, 5$) is the belief degree to which the R^h is believed to be the consequence for the h th rule with the combination of their parent nodes are stated as P_i , C_j and L_k . To simplify the CPT for the allision risk, the equivalence principle is used to construct the rule base set, which is given as followings:

BR_1 : IF P_1 and C_1 and L_1 , THEN $R^1 = \{(1, R_1), (0, R_2), (0, R_3), (0, R_4), (0, R_5)\}$,
 BR_2 : IF P_1 and C_1 and L_2 , THEN $R^2 = \{(0.67, R_1), (0.33, R_2), (0, R_3), (0, R_4), (0, R_5)\}$,
 \dots
 BR_{124} : IF P_5 and C_5 and L_4 , THEN $R^2 = \{(0, R_1), (0, R_2), (0, R_3), (0.33, R_4), (0.67, R_5)\}$,
 BR_{125} : IF P_5 and C_5 and L_5 , THEN $R^2 = \{(0, R_1), (0, R_2), (0, R_3), (0, R_4), (1, R_5)\}$,

The above set of rule base is established and then used to construct the CPT, which shows as Table 1.

2.3 Safety level prioritisation

In order to rank the safety level of the results, a novel of functions is assigned to calculate the belief degree distribution and the preference number PN of each state in L , C and P are defined with the range from 1 to 9. The preference number for nodes are assigned as $PN(L_1) = PN(C_1) = PN(P_5) = 9$, $PN(L_2) = PN(C_2) = PN(P_4) = 7$, $PN(L_3) = PN(C_3) = PN(P_3) = 5$, $PN(L_4) = PN(C_4) = PN(P_2) = 3$ and $PN(L_5) = PN(C_5) = PN(P_1) = 1$. Then a risk priority function is given as followings:

$PN(R_1 = poor) = PN(L_5) \times PN(C_5) \times PN(P_1) = 1 \times 1 \times 1 = 1$
 $PN(R_2 = fair) = PN(L_4) \times PN(C_4) \times PN(P_2) = 3 \times 3 \times 3 = 27$
 $PN(R_3 = average) = PN(L_3) \times PN(C_3) \times PN(P_3) = 5 \times 5 \times 5 = 125$
 $PN(R_4 = Good) = PN(L_2) \times PN(C_2) \times PN(P_4) = 7 \times 7 \times 7 = 343$
 $PN(R_5 = excellent) = PN(L_1) \times PN(C_1) \times PN(P_5) = 9 \times 9 \times 9 = 729$

Table 1. Conditional probability table with belief structures in FMEA

Rules	Antecedent attributes			Allision risk				
	The probability of allision (L)	Consequence severity (C)	chance of allision risk be detected (P)	Poor	Fair	Average	Good	Excellent
1	Very low	Negligible	Unlikely	0.33	0.000	0.00	0.00	0.67
2	Very low	Negligible	Reasonably unlikely	0.00	0.333	0.00	0.00	0.67
3	Very low	Negligible	likely	0.00	0.000	0.33	0.00	0.67
4	Very low	Negligible	Reasonably likely	0.00	0.000	0.00	0.33	0.67
5	Very low	Negligible	Definite	0.00	0.000	0.00	0.00	1.00
...
...
121	Very frequent	Catastrophic	Unlikely	1.00	0.00	0.00	0.00	0.00
122	Very frequent	Catastrophic	Reasonably unlikely	0.67	0.33	0.00	0.00	0.00
123	Very frequent	Catastrophic	likely	0.67	0.00	0.33	0.00	0.00
124	Very frequent	Catastrophic	Reasonably likely	0.67	0.00	0.00	0.33	0.00
125	Very frequent	Catastrophic	Definite	0.67	0.00	0.00	0.00	0.33

Table 2. Expert judgements under different vessel categories

Vessel categories	Experts No.	Judgement results		
		L	C	P
Fishing vessel	E1	0.4,0.6,0.8,0.9	0.1,0.15,0.2,0.45	0.2,0.3,0.45,0.55
	E2	0.6,0.7,0.75	0.1,0.2,0.5	0.2,0.3,0.5
	E3	0.8	0.5	0.15
Service vessel	E1	0.75,0.8,0.85,0.95	0.25,0.4,0.5,0.55	0.35,0.45,0.65,0.85
	E2	0.8,0.9,1	0.05,0.2,0.4	0.25,0.55,0.75
	E3	0.9	0.15	0.45
Tanker	E1	0,0.05,0.15,0.2	0.65,0.7,0.85,0.95	0.65,0.7,0.85,0.95
	E2	0,0.15,0.2	0.45,0.8,0.9	0.5,0.7,0.95
	E3	0.05	0.95	0.85
General cargo vessel	E1	0,0.05,0.15,0.2	0.45,0.6,0.7,0.95	0.6,0.8,0.9,1
	E2	0,0.25,0.3	0.5,0.75,0.9	0.7,0.75,0.95
	E3	0.1	0.6	0.7
Passenger vessel	E1	0.25,0.45,0.5,0.55	0.65,0.75,0.8,0.95	0.65,0.7,0.85,0.95
	E2	0.05,0.25,0.45	0.55,0.6,0.85	0.4,0.65,0.7
	E3	0.2	0.75	0.55

and

$$SL = \sum_{m=1}^5 \beta(R_m) \times PN(R_m) \tag{1}$$

where the *SL* means the safety level index. A higher safety level means low risk of allision, the opposite result means a high risk of vessel allision.

3 IMPLICATION AND DISCUSSION

The above introduced methods are used to investigate the vessel allision risk near the OWF under different categories. According to the categories given in AIS records, vessels are grouped as 'the fishing vessel', 'the service vessel', 'the tanker', 'the general cargo vessel' and 'the passenger vessel'. A group of three experts from different background are invited to provide a subjective evaluation of the allision risk of every vessel type. To test the transformation technology introduced in section 2.1, the experts are asked to give their judgement under a different format. The judgement result set is presented as Table 2.

By using the fuzzy transformation technology, judgement results can be transformed into the CPT for *L*, *P* and *C*, which given as Table 3, Table 4 and Table 5:

Table 3. CPT for node 'probability of allision'

States of L	Vessel categories				
	Fishing	Service	Tanker	General	Passenger
Very low	0.0000	0.0000	1.0000	1.0000	0.2500
Low	0.0000	0.0000	0.0000	0.0000	0.4722
Average	0.1111	0.0000	0.0000	0.0000	0.2778
Frequent	0.7222	0.0000	0.0000	0.0000	0.0000
Very frequent	0.1667	1.0000	0.0000	0.0000	0.0000

Table 4. CPT for node 'consequence severity'.

States of C	Vessel categories				
	Fishing	Service	Tanker	General	Passenger
Negligible	0.2778	0.3833	0.0000	0.0000	0.0000
Marginal	0.4444	0.3667	0.0000	0.0000	0.0000
Moderate	0.2778	0.2500	0.0556	0.2391	0.0000
Critical	0.0000	0.0000	0.5000	0.7174	0.7833
Catastrophic	0.0000	0.0000	0.4444	0.0435	0.2167

Table 5. CPT for node 'chance of allision risk undetected'.

States of P	Vessel categories				
	Fishing	Service	Tanker	General	Passenger
Unlikely	0.2143	0.0000	0.0000	0.0000	0.0000
Reasonably unlikely	0.6429	0.1151	0.0000	0.0000	0.0000
Likely	0.1429	0.5992	0.0000	0.0000	0.5833
Reasonably likely	0.0000	0.2857	0.5833	0.4444	0.3056
Definite	0.0000	0.0000	0.4167	0.5556	0.1111

When introducing the CPTs into the BN model, the conclusion of each vessel categories can be generated and presented as a format of the posterior probability distribution. For instance, the allision risk for fishing vessel is distributed as (0.13 (poor), 0.46 (fair), 0.18 (average), 0.15 (good), 0.09 (excellent)), which is graphical given in Figure 5.

In the similar way, results for other four vessel categories are 'service vessel = (0.33 (poor), 0.04 (fair), 0.28 (average), 0.22 (good), 0.13 (excellent))', 'tanker = (0.15 (poor), 0.17 (fair), 0.02 (average), 0.19 (good), 0.47 (excellent))', 'general cargo vessel = (0.01 (poor), 0.24 (fair), 0.08 (average), 0.15 (good), 0.52 (excellent))', 'passenger vessel = (0.07 (poor), 0.26 (fair), 0.29 (average), 0.26 (good), 0.12 (excellent))', see Figure 6.

The functions introduced in section 2.3 are used to prioritise the vessel allision risk on different categories based on the distribution result. For example, the SL for the type of fishing vessel is calculated as followings:

$$SL_{fishing} = 0.13*1 + 0.46*27 + 0.18*125 + 0.15*343 + 0.09*729 = 152.11$$

Similar computations are performed for other four vessel categories in the study, which are $SL_{service} = 204.49$, $SL_{tanker} = 417.91$, $SL_{general} = 445.25$, $SL_{passenger} = 219.48$. Consequently, the allision risk of each vessel category are ranked as 'fishing vessel' > 'service vessel' > 'passenger vessel' > 'tanker' > 'general cargo vessel'. The ranking result indicates the type of fishing vessels requires more attention to control the allision risk than other vessel categories. The belief degree distribution for L , C and P on the fishing vessel can present a more information. The Figure 5 shows although the fishing vessel has a low collision consequence, but fishing vessels has a higher probability of allision and low probability of risk detection before allision. Consulting the experts, this state is explained as two main reasons. In the study OWF area, many fishing vessels takes a fishing operation inside the OWF area, which is very close to the turbine structures and facilities. It leads to a very high collision risk if fishing vessels loss their control due to the machine failure or bad weather occurred. Meanwhile, another reason is the ability of detecting the risk for the fishing vessel is insufficient, which may due to the insufficient training or lack of facilities, which all leading to a low the probability of detecting the collision risk.

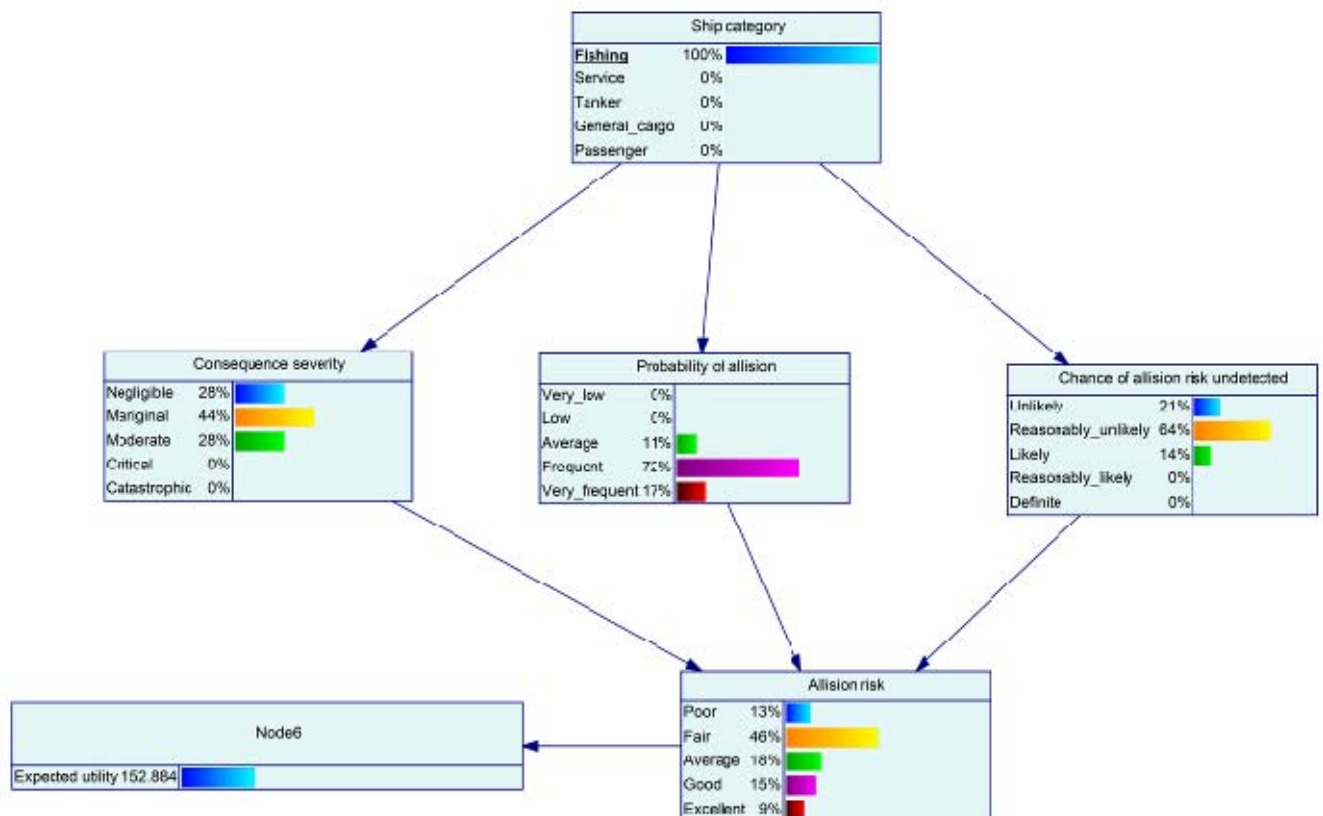


Figure 5. Analysis result for the fishing vessel in BN

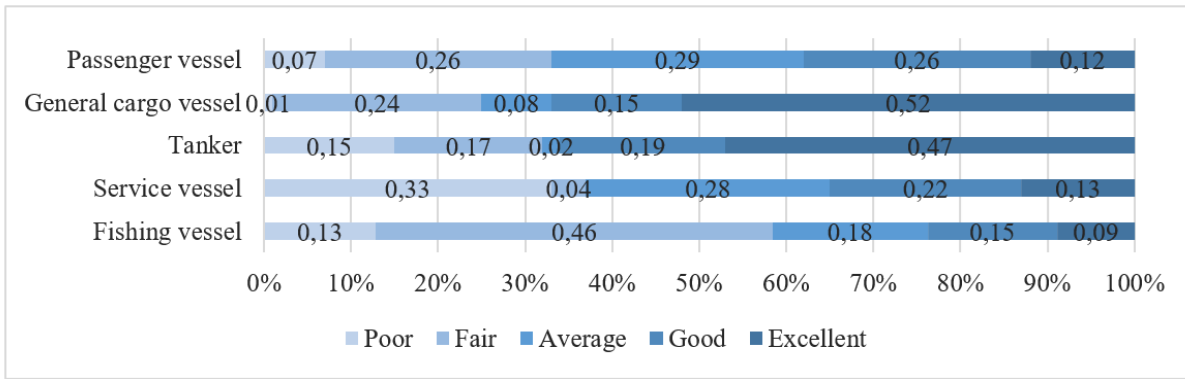


Figure 6. Allision risk distribution on vessel categories

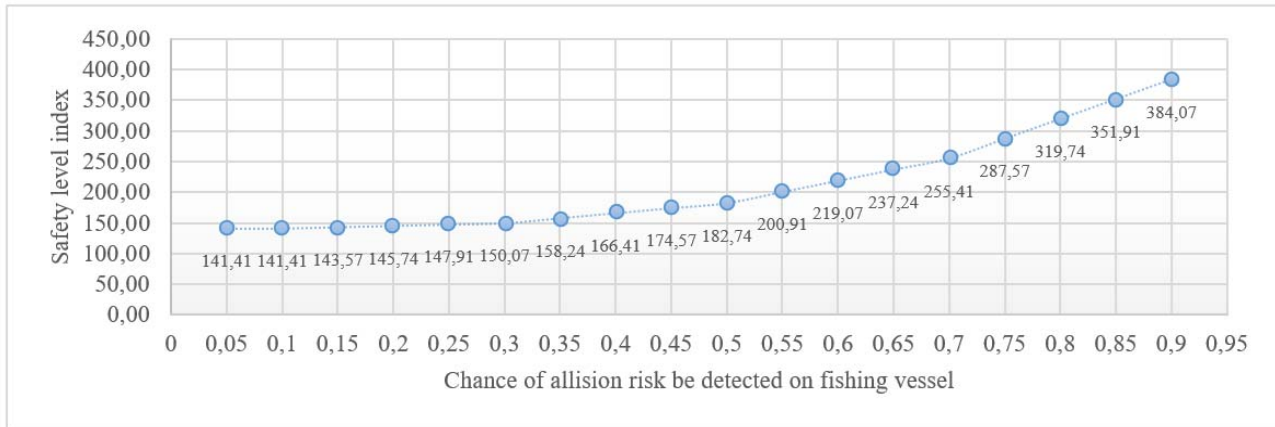


Figure 7. Sensitivity analysis of the chance of risk be detected on the type of fishing vessels.

The sensitivity analysis is used to test the effect of P on the fishing vessel. We assume there is a security control option is implemented on the fishing vessel to improve the risk detection probability. The security control options include improving training, equipping with the collision warning system, etc. To take a sensitivity analysis, we first set the node vessel category as '100% of the fishing vessel in the BN model. Then the belief degree of P is equivalently increased from 0.05 to 0.1, which means the detection probability for fishing vessel increasing from 100% of unlikely to 100% of definite. As a result (see Figure 7), the SL increased from 141.41 to 384.07, which shows a significant increase in safety level for this type of vessel. When belief degree of P less than 0.5, the influence degree of P to the conclusion is slight, which increased from 141.41 to 182.74. The influence degree of P to the safety level is significant when P larger than 0.5. It increased the safety level index from 182.74 to 384.07. Therefore, the result states that security control options can improve the safety level for vessels. It is necessary to ensure the belief degree of P for fishing vessels not smaller than 0.5, which mean not worse than the state as 'likely'. However, this sensitivity analysis can be also used to test the influence of risk factors on other vessel categories, which is worth to analysis in the further study.

4 CONCLUSION

This paper introduced a fuzzy rule-based BN model based on FMEA analysis. In this model, the fuzzy mapping and the rule base technology are to transform the subjective judgement into conditional probabilities. Three belief factors are developed to model the relationship between the allision risk level associated with its risk attributes L , C and P that based on the FMEA analysis.

The proposed framework is then applied to analyse the vessel allision risk near the OWF under different categories. In order to facilitate the study, a group of three experts has been invited to give judgement under various format shapes. Through the fuzzy mapping and transforming technology, the judgement is then used to provide the conditional probability table for each risk factors of L , C and P in the BN model. A set of rule bases is given to link each risk factor to the conclusion of allision risk. The obtained posterior probability distributions under different vessel categories are then computed to priorities the safety level, and sensitivity analysis is implemented at last.

When applying this BN model in practice, the result shows the category of the fishing vessel has the highest allision risk than the other four types of vessels. Fishing vessels have a high probability of collision and a low chance of detecting the risk before allision. Meanwhile, the type of service vessel is ranked as the second and following with the passenger vessel, the tanker and the general cargo

vessel. Influence degree of risk detection on the fishing vessel is analysed, the result shows that some security control options such as equipping the early warning system, providing safety training can reducing the vessel allision risk.

This paper discussed the probability of using a rule-based BN model to analyse the vessel allision risk near the OWF when using the expert judgement. An example of studying vessel allision risk is given to test the reliability of the model. However, there are some insufficiencies should be studied in further analyses. The example in this paper is simple and general. Enhancing the BN structure can significantly improve the usage of the BN model. Methods of mitigating the bias in the expert judgement are required, which not discussed in this paper. Other security control options can be tested and prioritised by using the BN model, which can provide support for risk prevention and safety control.

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