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A quantified risk analysis for oil spill during crude oil loading operation on tanker ship under improved Z-number based Bayesian Network approach

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ABSTRACT

Crude oil cargo operation poses significant oil spill risk although utmost care is exercised by ship and shore crew. This paper focuses on quantitative risk analysis for oil spill incidents in crude oil tanker ships to enhance safety at the operational level and prevent potential pollution. To achieve this purpose, the Bayesian network (BN) is used under the improved Z-numbers theory. While BN provides a powerful tool based on cause and effect network between the variables, the improved Z-numbers are capable of handling uncertainty and improving the reliability of qualitative expert judgments. The findings show that the occurrence probability of oil spill risk in crude oil tanker ships is found 2.90E−02 during the cargo loading operation. The findings of the research are expected to contribute ship crew, safety inspectors, ship owners, HSEQ managers, and terminal managers in risk management decision-making, improving operational safety, taking control actions, and minimizing oil spills.

1. Introduction

Crude oil cargo transportation at sea has significantly increased over the years due to the large oil demand in the world. The statistics have shown that crude oil cargo carriage by tanker ships has gradually increased almost doubling from the 1990s to the 2000s (ITOPF, 2020). The demand of crude oil shipment has increased the number of tanker ships, vessel traffic, and terminal cargo operations (Cakir et al., 2021; Ye et al., 2019). These circumstances drastically may cause catastrophic oil spill risk at sea or port since it has raised concerns about the marine environment, human life and marine ecosystem (Sevgili et al., 2022; Aydin et al., 2021a). Although significant national and international rules and conventions on preventing oil spills were adopted in the last decades in the maritime industry, oil spill incidents still keep occurring. There have been significant accidents recorded as major oil spills involving tanker ships such as Amoco Cadiz, Exxon Valdez, Independenta, Erika, Sanchi, Wakashio and New Diamond where thousands of tonnes of crude oil spills into the sea and crew members lost their lives (Cakir et al., 2021). The maritime regulatory body, IMO (International Maritime Organisation), has adopted various codes and conventions such as MARPOL (International Convention for the Prevention of Pollution from Ships), INTERVENTION (International Convention Relating to Intervention on the High Seas in Cases of Oil Pollution Casualties), OPRC (International Convention on Oil Pollution Preparedness, Response and Co-operation), CLC (International Convention on Civil Liability for Oil Pollution Damage), etc. to minimize oil pollution risk at sea, but oil spill accidents are still on-going (Akyuz and Celik, 2018). Although the amount of cases slightly decreased compared to the last decades, a significant concern is still rising about oil spill risk due to catastrophic consequences to the marine environment.

In the last decades, studies concerning ship-sourced oil spills have been conducted since a clean marine environment is of paramount importance for the sustainability of ecosystems. Some significant researchers focused on the detection, tracking and monitoring of oil spills on sea areas (Huang et al., 2022; Marta-Almeida et al., 2013; Moroni et al., 2019; Nieto-Hidalgo et al., 2018; Shirvany et al., 2012; Vinoth Kumar et al., 2020), as well as oil spill simulation and emergency response planning (Cabrera Aguilera et al., 2016; Fetissov et al., 2021; Kang et al., 2016; Wu et al., 2020; Ye et al., 2019), as accurate detection and appropriate response plan may help authorities to deal with oil spills correctly and timely.

Another research approach is evaluating ship accidents as a cause of oil spills, such as collision and grounding, or structural damage due to heavy weather conditions (Cakir et al., 2021; Chen et al., 2019; Chen

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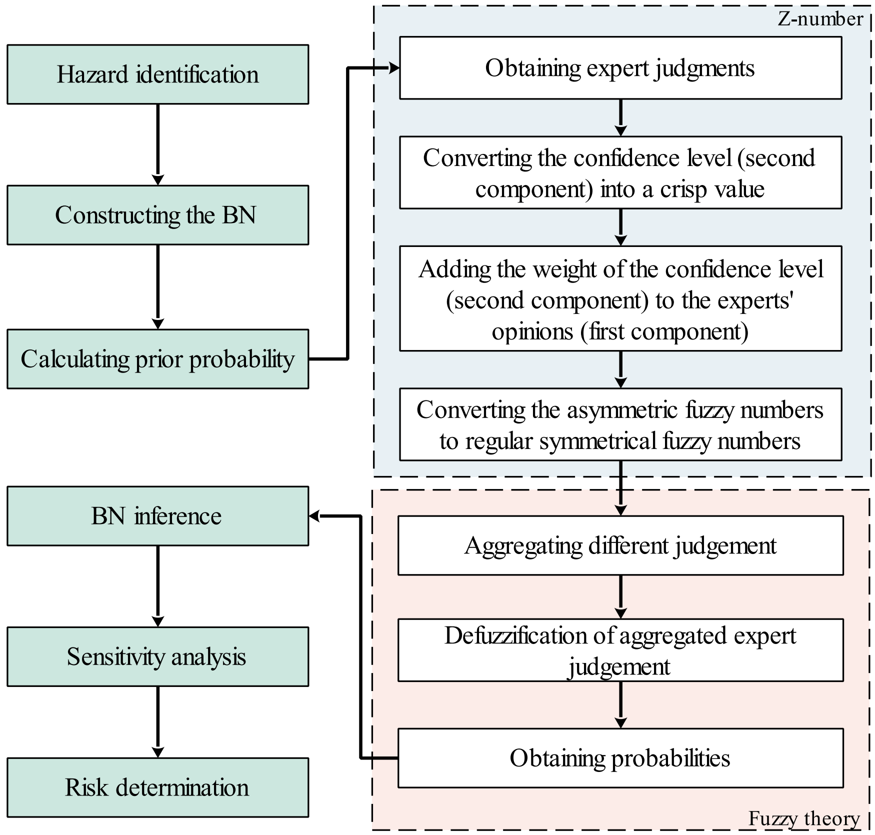

Fig. 1. Conceptual framework of the improved Z-number based Bayesian network.

et al., 2020; Han et al., 2018; Rajendran et al., 2022; Rogowska and Namieśnik, 2010; Yildiz et al., 2021). Oil spills due to such ship accidents can be in large quantities with respect to the categorization of the International Tanker Owners Pollution Federation (ITOPF) about the oil spills by size, <7 tonnes (small), 7–700 tonnes (medium) and >700 tonnes (large) (ITOPF, 2023). Although large spills attract significant attention, the number of small and medium spills is greater than them. Most of the spill cases are caused by small and medium sizes (7–700 tonnes) and those occur due to reasons such as cargo operations, bunkering, and other shipboard processes. ITOPF also reports that 29 % of small to medium size oil spills were realized during the cargo operations, between 1970 and 2022 (ITOPF, 2023). In this context, cargo operations are critical activities in the aspect of marine environment safety. The literature has studies researching the oil spill risks onboard vessels (Akhtar et al., 2012; Akyuz and Celik, 2018; Amir-Heidari et al., 2019; Chen et al., 2018; Goerlandt and Montewka, 2015), however, there is a research gap concerning the analysis of oil spill risks during cargo operations. Therefore, this paper aims to research oil spill risk analysis on crude oil tanker ship by dealing with its cargo loading operation. In this context, a novel methodology, the improved Z-number based Bayesian network approach, is proposed. The risks were analyzed through the Bayesian Network approach since it is a robust tool that helps to understand the cause and effect between the variables. Besides, improved Z-numbers and fuzzy sets theory were utilized to overcome uncertainty and vagueness in the stage of expert judgment evaluation. In this section, the oil spill phenomenon in maritime transportation is evaluated and the need of oil spill risk analysis during tanker cargo operation is explained. Section 2 introduces the methodologies applied in the paper. Section 3 includes the integration of methodologies while Section 4 presents the application steps for the risk analysis. Finally, Section 5 concludes the paper.

2. Research methodology

This section briefly introduces methods used in the paper and how to integrate them for detailed risk analysis.

2.1. Fuzzy sets theory

Fuzzy sets provide a practical solution to analyze process where uncertainty, ambiguity and subjectivity are prevalent in decision-making problems. It is capable of handling the challenges of inadequacy data-set by performing experiments (Çevik and Arslan, 2022; Erdem and Akyuz, 2021; Aydin et al., 2021b). Utilizing of fuzzy sets can be basically described as a calculation performed with words (Jiskani et al., 2022). The fuzzy sets applications have been widely used in various industries such as nuclear, petrochemical, automotive, aviation, transportation, etc. to deal with subjectivity and vagueness in the decision-making process (Singh et al., 2022; Maalouf and Hoque, 2022; Elidolu et al., 2022; Karaca et al., 2022; Liu et al., 2021; Uflaz et al., 2023). Fuzzy sets provide a gradual transition among the concepts under adopting fuzzy membership functions introducing the linguistic statements (Ford et al., 2016). In the process, experts provide linguistic judgments as inputs, then they are transformed into membership functions. Triangular and trapezoidal fuzzy set numbers are widely used in decision-making problems.

2.2. Z-number theory

Since humans are willing to use natural language to express their preferences in the decision-making process, this may bring challenges as it is imprecise. To remedy this gap, Zadeh (2011) introduced the Z-numbers theory to demonstrate imperfect information where fuzzy numbers can be considered as paired like that the partly information is fundamentally processed (Alam et al., 2023). The Z-numbers theory is a robust approach to show certain decision information in the decision-making process. It helps to enhance the reliability of the decision information and provides more reasonable results. There have been some significant applications adopted Z-numbers in different disciplines to solve uncertainty related with decision-making problems such as the food industry (Abiyev et al., 2018), logistics (Aboutorab et al., 2018), petrochemical industry (Yazdi et al., 2019), civil engineering industry (Akhavein et al., 2021), mining industry (Jiskani et al., 2022), etc. In view of that, Z-number theory takes the probability of reliance on the judgment of experts into consideration and yields more reliable outcomes for the research.

A Z-number consists of a fuzzy pair of numbers expressed as $Z = \left(\widetilde{A}, \widetilde{B}\right)$. The first component of the Z-number, $\widetilde{A}$ is a restriction (experts' opinions) and is represented as $\widetilde{A} = \{x, \mu_{\widetilde{A}}(x) | x \in [0,1]\}$. The second component $\widetilde{B}$ reflects the reliability (confidence level) and is represented as $\widetilde{B} = \{x, \mu_{\widetilde{B}}(x) | x \in [0,1]\}$. $\mu_{\widetilde{A}}$ and $\mu_{\widetilde{B}}$ are membership functions of $\widetilde{A}$ and $\widetilde{B}$, respectively (Zadeh, 2011).

2.3. Bayesian network

Bayesian network (BN) is one of the robust mathematical modelling in risk analysis to represent causal relationships between the random variables. To achieve this purpose, conditional probabilities of each node are required (Wu et al., 2023; Sezer et al., 2023). Directed acyclic graph (DAG) is substantial terminology to define the arc between each pair of nodes in the BN structure (Kamal and Aydın, 2022). In the BN, nodes with edges directed into them are called "child" nodes, likewise the nodes going outside links are "parent" nodes. In case nodes do not have any parents in the structure, they are called "root" nodes, and the node that does not have a child is a "leaf" node (Zhang and Mahadevan, 2021; Khan et al., 2020; Khakzad et al., 2011). The simple Bayesian network model is presented in Fig. A.1. The fundamental background of the BN is based on the chain rule, which is tackling with the joint probability distribution of variables. The chain rule basically defines the marginal and conditional probabilities for each node in the BN structure (Aydin et al., 2021b). According to the rule, the calculation of marginal and conditional probabilities for each node can be defined as $U = \{X_1, X_2 \dots X_n\}$, which is called as variables, and the joint probability of the variable *Xi* is calculated as (Jensen and Nielsen, 2007);

$$P(U) = \prod_{i=1}^{n} P(X_i | P_a(X_i)) \tag{1}$$

In Eq. (1), $P_a(X_i)$ denotes the parent set of variables in the case of $j \neq i$.

3. Integration of methodologies

In this section, the integration of methods is explained step by step to perform a comprehensive risk analysis. The conceptual framework of the method integration is illustrated in Fig. 1.

3.1. Constructing the BN model

The BN model is established by considering the risk in the researched subject. Firstly, appropriate root nodes for the identified risk are determined. Then all root nodes are categorized and the proper intermediate node is determined for each root node. Also, other intermediate nodes can be identified by classifying intermediate nodes. Next, intermediate nodes are determined that point directly to the leaf node and contribute mainly to the leaf node. The leaf node is the top event that expresses the defined risk (Guo et al., 2021). In the constructed BN model, the states of each node are determined. Each node has a relationship to the probability distribution of the states of its parent nodes. Conditional probability tables (CPTs) illustrate the casual relationship between parent and child nodes. CPTs express the strength and type of conditional dependencies between two nodes in BN (Zarei et al., 2019). Accordingly, CPTs are derived for intermediate nodes and leaf node.

Table 1
Linguistic terms for the restrictions component of the Z-number.

Linguistic term	Trapezoidal fuzzy numbers
Very low (VL)	(0, 0, 0.1, 0.2)
Low (L)	(0.1, 0.2, 0.2, 0.3)
Slightly low (SL)	(0.2, 0.3, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.5, 0.6)
Slightly high (SH)	(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, 1)

Table 2
Linguistic terms for the reliabilities component of the Z-number.

Linguistic term	Trapezoidal fuzzy numbers
0 % sure	(0, 0, 0.025, 0.05)
5 % sure	(0.025, 0.05, 0.075, 0.1)
10 % sure	(0.075, 0.1, 0.125, 0.15)
15 % sure	(0.125, 0.15, 0.175, 0.2)
20 % sure	(0.175, 0.2, 0.225, 0.25)
25 % sure	(0.225, 0.25, 0.275, 0.3)
30 % sure	(0.275, 0.3, 0.325, 0.35)
35 % sure	(0.325, 0.35, 0.375, 0.4)
40 % sure	(0.375, 0.4, 0.425, 0.45)
45 % sure	(0.425, 0.45, 0.475, 0.5)
50 % sure	(0.475, 0.5, 0.525, 0.55)
55 % sure	(0.525, 0.55, 0.575, 0.6)
60 % sure	(0.575, 0.6, 0.625, 0.65)
65 % sure	(0.625, 0.65, 0.675, 0.7)
70 % sure	(0.675, 0.7, 0.725, 0.75)
75 % sure	(0.725, 0.75, 0.775, 0.8)
80 % sure	(0.775, 0.8, 0.825, 0.85)
85 % sure	(0.825, 0.85, 0.875, 0.9)
90 % sure	(0.875, 0.9, 0.925, 0.95)
95 % sure	(0.925, 0.95, 0.975, 1)
100 % sure	(0.975, 1, 1, 1)

3.2. Calculating prior probability

Prior probabilities are assigned for root nodes in the constructed BN model. To obtain prior probabilities, the Z-number-based fuzzy theory approach is applied. Thus, uncertainty and lack of data can be dealt with. In this context, expert opinion elicitation is needed. The expert group first evaluates the probability of occurrence of the event (i.e. first part of Z-number) they evaluated according to the linguistic terms in Table 1. Then they use the reliability levels in Table 2 to determine their degree of certainty (i.e. second part of Z-number). Experts' evaluations are converted into trapezoidal fuzzy numbers according to Tables 1 and 2. Thus, the Z-number in $Z = [(a_1, a_2, a_3, a_4), (b_1, b_2, b_3, b_4)]$ the form containing two fuzzy sets is obtained from each expert (Yazdi et al., 2019; Jiskani et al., 2022). Then, the translation process from Z-number to fuzzy number is conducted. This process consists of three stages and is as follows (Kang et al., 2012).

Firstly, the second part of the Z-numbers, i.e. the confidence level, is converted to a crisp value by applying Eq. (2). Thus, non-fuzzy numbers, i.e. crisp values, can be obtained from trapezoidal fuzzy numbers. Converting fuzzy output into crisp output is defuzzification. Eq. (2) introduces the Center of Area, one of the widely used defuzzification techniques.

$$X^{*} = \int x \frac{\mu_{\widetilde{B}}(x) dx}{\int \mu_{\widetilde{B}} dx} \tag{2}$$

Then the first component (restriction) of the Z number is weighted by the second component (confidence level) and the weighted Z-number

($\widetilde{Z}^{\alpha}$) is represented as in Eq. (3). So, the weight of the confidence level is added to the expert opinions.

$$\widetilde{Z}^{\alpha} = \left\{x, \mu_{\widetilde{A}^{\alpha}(x)} | \mu_{\widetilde{A}^{\alpha}(x) = \alpha\mu_{\widetilde{A}}}, x \in [0,1]\right\} \tag{3}$$

where α denotes the crisp value of the second part of the Z numbers. In the final stage, asymmetric fuzzy numbers are converted to symmetrical fuzzy numbers. In this way, $\widetilde{Z}^{\alpha}$ becomes a symmetrical fuzzy number ($\widetilde{Z}^{'}$) as shown in Eq. (4).

$$\widetilde{Z}^{'} = \left\{x, \mu_{\widetilde{Z}^{'}(x)} | \mu_{\widetilde{Z}^{'}(x) = \mu_{\widetilde{A}}\left(\frac{x}{\sqrt{\alpha}}\right)}, x \in [0,1]\right\} \tag{4}$$

After obtaining fuzzy reliability judgments for each event from each expert, Eq. (5) is used to aggregate different opinions and acquire a common trapezoidal fuzzy number.

$$\widetilde{A}_i^{*} = (a, b, c, d) = \sum_{j=1}^{m} w_j{}^{*}\widetilde{A}_{ij}(a, b, c, d) \tag{5}$$

where $\widetilde{A}_{ij}$ represents the jth expert's opinion of the i_{th} event. w_j denotes the weight of the jth expert and the aggregated fuzzy number associated with the event i is denoted by the $\widetilde{A}_i^{*}$. $\widetilde{A}_i^{*}$ is in fuzzy form and Eq. (2) is applied for the defuzzification of $\widetilde{A}_i^{*}$.

Onisawa's (1988) Eqs. (6)–(7) are used to compute the occurrence probabilities of events (Pr). Thus, the prior probabilities of the root nodes containing the events are determined.

$$Pr = \begin{cases} \dfrac{1}{10^{K}}, X^{*} \neq 0 \\ 0, X^{*} = 0 \end{cases} \tag{6}$$

$$K = \left[\left(\frac{1 - X^{*}}{X^{*}}\right)\right]^{1/3} \times 2.301 \tag{7}$$

where X^{*} represents the crisp value of $\widetilde{A}_i^{*}$.

3.3. BN inference

In BN inference, causal and diagnostic inferences are executed. Causal inference of BN involves reasoning from root causes to effect and is the forward estimation process. In other words, the state probabilities of the leaf nodes are determined with the data taken from the root nodes. First, the prior probability of each root node and the CPTs of the intermediate and leaf nodes are considered. Next, the probability of each intermediate node and leaf node is calculated using the Bayes theorem (Li et al., 2019).

Contrary to casual inference, diagnostic inference is the process of reasoning from effect to cause. Diagnostic inference is a backward estimation method that aims to determine the probabilities of causes for a known result. In the diagnostic inference of BN, the undesired event is assumed to occur. Thus, based on new evidence, the prior probabilities of the variables are updated and the posterior probabilities of the variables are obtained (Yu et al., 2022).

3.4. Sensitivity analysis

Sensitivity analysis is a functional tool in the risk assessment process as it enables the identification of important parameters in the BN model. Sensitivity analysis determines the impact of each node on the failure of the leaf node. Thus, highly sensitive nodes representing the weak points of the system can be identified (Aydin et al., 2021b). Generally, the control variable method, which changes the failure probability of one node and keeps the failure probability of other nodes unchanged, is conducted for sensitivity analysis. In this context, the impact of the changed node is observed on the leaf node. The change in the failure probability of the leaf node is computed under different failure probabilities. So high-sensitivity nodes can be found (Guo and Wu, 2023).

Table 3
Nodes representation in the BN model.

Node classification	Symbol	Node definition	State
Leaf node	T	Oil spill	Yes, no
Intermediate node	M1	Cargo loading process-related failures	Yes, no
Intermediate node	M2	Oil overflow from the cargo tank	Yes, no
Root node	X1	Failure of the tank measurement system to monitor the oil surface level	Yes, no
Root node	X2	Inaccurate gauging of oil level from ullage line	Yes, no
Root node	X3	Failure of high level & overfill alarms	Yes, no
Intermediate node	M3	Inappropriate manifold arrangement	Yes, no
Root node	X4	Insecure connection between the cargo hose/arm to the ship's manifold	Yes, no
Root node	X5	Inadequate or improper provision of manifold drip tray	Yes, no
Root node	X6	Lines not drained after oil transfer	Yes, no
Intermediate node	M4	Faulty stowage and ballast operations	Yes, no
Root node	X7	Open condition/inadequate blinding of lines and valves of tanks not in the plan	Yes, no
Root node	X8	Improper tank stowage leading to unacceptable stress on the ship	Yes, no
Root node	X9	Failure in ballast water operation for ship's stability	Yes, no
Intermediate node	M5	Terminal-related failures	Yes, no
Root node	X10	Failure in the communication between the ship and the terminal	Yes, no
Root node	X11	Failure in the oil pumping system of the terminal in case of an emergency	Yes, no
Intermediate node	M6	Deficiency on deck arrangement	Yes, no
Root node	X12	Open-condition of deck scuppers	Yes, no
Root node	X13	Inadequacy of oil spill equipment	Yes, no

4. Quantitative risk analysis for oil spill during cargo loading operation on crude oil tanker

This section provides a quantitative risk analysis for oil spill incidents during cargo loading operations onboard crude oil tanker ships.

4.1. Cargo loading operation on crude oil tanker

Crude oil is a heavy black liquid that contains hydrocarbons, nitrogen, sulphur and various elements. When it contacts with the sea, particularly in coastal areas, it affects adversely individuals and marine ecosystems (NAP, 2022). It has a significant place in the world's trade over many years and is transported by means of tanker vessels (Hennig et al., 2012). It can be handled by tankers with a variety of sizes such as medium-range, long-range, Aframax, Suezmax etc. which are specifically designed for handling oil cargo. Considering its hazards, the safe and clean operation of crude oil is of critical importance for life, property and the marine environment.

The cargo operations are responsible for a considerable part of the global oil spills (ITOPF, 2023). In particular, cargo loading operation requires special attention due to the nature of the work. The crude oil is pumped by the terminal's discharge pumping system, it flows through the pipes and reaches the ship's manifold. Then, it continues to flow in

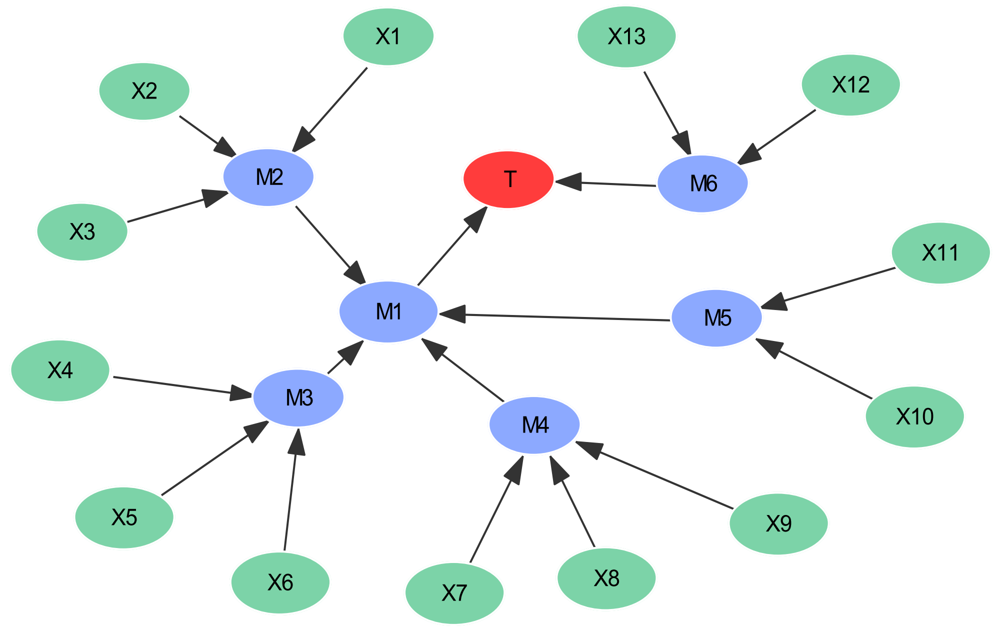

Fig. 2. A general BN for oil spill risk.

Table 4
CPT of intermediate node M2 "Oil overflow from cargo tank".

X1		Yes				No			
X2		Yes		No		Yes		No	
X3		Yes	No	Yes	No	Yes	No	Yes	No
M2	Yes	0.978	0.933	0.911	0.728	0.911	0.689	0.639	0.051
	No	0.022	0.067	0.089	0.272	0.089	0.311	0.361	0.949

the ship's pipelines and finally is stored in the cargo tanks. However, these stages involve various operational risks that may lead to a shipboard oil spill. A spill can occur due to overflow of oil from cargo tanks, arrangement of manifold area inappropriately, as well as problems in cargo stowage and ballast operations, and terminal-related failures during emergencies. Besides, in case of a deficiency or failure in deck arrangements such as the condition of deck scuppers or oil spill equipment, the oil may be overboarded and cause pollution on the sea. Therefore, all stages of cargo loading operation should be performed by taking into account potential risks (ISGOTT, 2020).

4.2. Predicting oil spill risk

BN is established to analyze the risk of oil spills during loading on crude oil tankers and to identify related significant root causes systematically. Oil spill risk is the leaf node of BN. In this context, root nodes and intermediate nodes are determined with the support of expert opinions by considering the accident reports, international guidelines, literature review (Aydin et al., 2021a; ISGOTT, 2020; SIAF, 2017). Table 3 presents the representation of the nodes in the BN. On the other hand, while constructing the BN, the interdependence relationships between the nodes are expressed through arcs. The BN model of the oil spill risk is shown in Fig. 2. In Fig. 2, the red node is the leaf node, the blue nodes are the intermediate node and the green nodes represent the root nodes. In the BN model, CPTs are defined based on the experts' knowledge and experience. Table 4 shows an example of a CPT between root nodes X1 (Failure of the tank measurement system to monitor the oil surface level), X2 (Inaccurate gauging of oil level from ullage line) and X3 (Failure of high level & overfill alarms) and intermediate node M2 (Oil overflow from the cargo tank).

The inputs of the root nodes of the established BN are prior probabilities. A Z-number-based fuzzy theory approach, which uses multi-expert judgments, is applied to calculate prior probabilities. In this context, nine experts who have participated in the loading operation on crude oil tanker ships many times and have extensive knowledge and experience about the loading operation are invited to calculate the prior probabilities of each root node. The expert group consists of equally weighted academicians, masters, and company operation managers and Table 5 shows their basic information. Experts express their opinions on the probability of each root node (considering Table 1) and the confidence level (considering Table 2) regarding their opinions. Judgments from experts are listed in Table 6. Then, using Eqs. (2)–(7), prior probabilities are calculated. To better explain the computational processes in the proposed methodology, a root node X1(Failure of the tank measurement system to monitor oil surface level) is taken in Table 7 as an example. Consequently, aggregated fuzzy numbers, their crisp values and estimated prior probabilities for each root node are provided in Table 8.

After the prior probabilities are calculated, the inference process is performed. In this paper, Genie software is used for BN inference. In BN, causal inference is based on CPTs and prior probabilities. The intermediate and leaf node probability calculated as a result of causal inference is shown in Fig. 3. According to Fig. 3, the risk of the oil spill is 2.90E−02. Assuming that the oil spill occurs, i.e. $P(T = Yes) = 1$, the diagnostic inference is performed and the posterior probability of the root nodes is obtained. Table 9 lists the posterior probabilities of the root nodes.

Sensitivity analysis is carried out to identify critical parameters in the BN model. The probability of the root node Xi is changed to 1 and 0. The probability of the oil spill occurring for both states i.e. $P(T|Xi = Yes)$ and

Table 5
Marine experts participated in the study.

Expert	Position	Education	Experience	Information
1	Oceangoing master	BSc.	9 years	This expert actively works onboard tanker vessels and performs crude oil cargo operations frequently.
2	Oceangoing chief officer	BSc.	8 years	This expert performed cargo operations onboard oil and chemical tankers. Most of his experience is about crude oil typed vessels.
3	Oceangoing chief engineer	BSc.	8 years	He works onboard crude oil tanker ships and is responsible for ship machinery systems including cargo equipment. He has wide knowledge and experience concerning crude oil cargo operations.
4	Oceangoing watchkeeping officer	MSc.	6 years	This expert worked onboard oil tankers and was involved in cargo operations by performing the loading and discharging of the tanks as per chief officers' directions. She has knowledge and experience in cargo operation systems.
5	Technical inspector	BSc.	10 years	He has experience onboard as a chief engineer. He was involved many crude oil operations on tankers and now he works in a tanker ship company and manages the fleet's technical program.
6	Operational manager	BSc.	8 years	This expert worked on oil tankers as a chief officer was responsible from cargo operations. He started to work onboard a tanker company. He is responsible to manage the fleet's operational program.
7	Safety inspector	BSc.	10 years	This expert worked on crude oil tankers as an oceangoing master, had involved many cargo operations. He works on an international tanker company and deals with health, safety and environmental issues.
8	Safety inspector	BSc.	9 years	He worked on tankers as oceangoing chief officer and now started to work on a tanker company. He is responsible for managing the fleet's health, safety, and environmental program.
9	Academician	PhD.	6 years	She worked on oil tankers as chief officer and was responsible for cargo operations. She conducts research concerning risk analysis on maritime transportation at a technical university.

$P(T|Xi = No)$ is calculated. Fig. 4 illustrates the sensitivity analysis results of root nodes.

On the other hand, as a result of the calculation without taking into account the confidence level, i.e. without the Z-number, the oil spill risk is found as 3.12E−02. When the result of the conventional fuzzy-based approach is compared with the Z-number theory, there is a distinct increase in the risk of oil spills. Also, according to Table 10, when Z-number theory is taken into consideration, it is seen that the prior probabilities change clearly. This may affect the outcome of the research. For example, X1 has the third-highest prior probability when the confidence level is considered, while it has the fourth-highest prior probability when the confidence level is not taken into account. The rate of change may increase or decrease slightly more depending on the confidence level assessments made by experts. This paper uses the Z-number approach, which considers the confidence level of experts and can minimize the shortcomings of partial and imprecise knowledge from experts.

4.3. Model validation

Validation is a significant aspect of the validity of the subjectively constructed model, as it provides a reasonable amount of reliability in the outcomes. Jones et al. (2010) proposed a three-axiom sensitivity analysis for the model's partial validation. Axiom 1: Relative increases or decreases in the posterior probabilities of the child nodes should undoubtedly follow from minor changes in the prior subjective probabilities of each parent node. Axiom 2: The consistency of the subjective probability distributions of each parent node should be maintained in the influence magnitude of the child node values. Axiom 3: There should always be a bigger total influence size from the combination of the probability fluctuations from the x attributes on the values than from the set of x-y (y∈x) attributes.

To test the requirements of Axiom 1, the impact of changes in each parent node on each child node is observed. For this, the M1 node shown in Table 11 is chosen as an example. Table 11 gives the effect of nodes X1, X2, and X3 on node M1. Accordingly, if the X1 node occurs, the probability of the M2 node occurring increases from 6.6 % to 73 %. If X1

Table 6
Experts' evaluations for root nodes.

Node		E1	E2	E3	E4	E5	E6	E7	E8	E9
X1	Probability	H	SH	SL	VH	M	SH	H	SH	H
	Reliability	85	85	75	95	80	90	85	90	80
X2	Probability	SH	SH	M	VH	M	SH	M	M	SH
	Reliability	90	70	75	95	80	90	85	75	80
X3	Probability	SH	SH	H	M	L	SL	M	M	SL
	Reliability	95	75	90	75	80	85	80	85	95
X4	Probability	M	H	H	SH	SH	M	H	SH	H
	Reliability	90	75	80	85	85	85	75	85	80
X5	Probability	M	L	SH	M	SH	M	SL	SL	L
	Reliability	95	70	70	65	80	90	85	75	80
X6	Probability	SH	M	M	SL	H	M	SH	M	SH
	Reliability	80	85	75	85	85	80	80	85	85
X7	Probability	M	SH	M	L	H	SL	M	SH	M
	Reliability	85	75	80	65	90	85	85	80	80
X8	Probability	SL	M	SL	VL	SH	M	SL	SL	M
	Reliability	85	75	65	75	80	90	85	90	70
X9	Probability	L	SH	SL	VL	SH	M	SL	L	SL
	Reliability	85	75	70	75	80	85	80	85	75
X10	Probability	H	SH	H	H	VH	SH	H	H	SH
	Reliability	90	75	90	80	90	85	90	85	90
X11	Probability	L	SL	M	SH	M	SL	L	L	SL
	Reliability	85	70	70	75	80	85	80	85	90
X12	Probability	SH	M	VH	VH	M	H	H	SH	M
	Reliability	80	90	95	95	80	90	85	80	85
X13	Probability	SL	M	SH	H	VL	SL	L	SL	M
	Reliability	85	75	75	70	80	95	85	75	80

Table 7
The process of computation of the probability of X1.

Experts' opinions on the probability of root node occurrence		
Expert	Evaluation	Fuzzy numbers
E1	H	(0.7, 0.8, 0.8, 0.9)
E2	SH	(0.5, 0.6, 0.7, 0.8)
E3	SL	(0.2, 0.3, 0.4, 0.5)
E4	VH	(0.8, 0.9, 1, 1)
E5	M	(0.4, 0.5, 0.5, 0.6)
E6	SH	(0.5, 0.6, 0.7, 0.8)
E7	H	(0.7, 0.8, 0.8, 0.9)
E8	SH	(0.5, 0.6, 0.7, 0.8)
E9	H	(0.7, 0.8, 0.8, 0.9)

Experts' opinions on the degree of certainty		
Expert	Evaluation	Fuzzy numbers
E1	85	(0.825, 0.85, 0.875, 0.9)
E2	85	(0.825, 0.85, 0.875, 0.9)
E3	75	(0.725, 0.75, 0.775, 0.8)
E4	95	(0.925, 0.95, 0.975, 1)
E5	80	(0.775, 0.8, 0.825, 0.85)
E6	90	(0.875, 0.9, 0.925, 0.95)
E7	85	(0.825, 0.85, 0.875, 0.9)
E8	90	(0.875, 0.9, 0.925, 0.95)
E9	80	(0.775, 0.8, 0.825, 0.85)

Converting the second component into a crisp value (applying Eq. (2))		
Expert	Crisp value of the degree of certainty (α)	$\sqrt{\alpha}$
E1	0.863	0.929
E2	0.863	0.929
E3	0.763	0.873
E4	0.963	0.981
E5	0.812	0.901
E6	0.913	0.955
E7	0.863	0.929
E8	0.913	0.955
E9	0.812	0.901

Adding the weight of the second component to the first component and obtaining regular fuzzy numbers (applying Eqs. (3) and (4))	
Expert	Experts' fuzzy reliability judgments
E1	(0.650, 0.743, 0.743, 0.836)
E2	(0.464, 0.557, 0.650, 0.743)
E3	(0.175, 0.262, 0.349, 0.437)
E4	(0.785, 0.883, 0.981, 0.981)
E5	(0.361, 0.451, 0.451, 0.541)
E6	(0.478, 0.573, 0.669, 0.764)
E7	(0.650, 0.743, 0.743, 0.836)
E8	(0.478, 0.573, 0.669, 0.764)
E9	(0.631, 0.721, 0.721, 0.811)

Aggregated experts' opinions (applying Eq. (5))	(0.519, 0.612, 0.664, 0.746)
Crisp value (applying Eq. (2))	0.635
Probability (applying Eqs. (6) and (7))	1.22E−02

Table 8
Z-number-based fuzzy theory approach results.

Node	Aggregated fuzzy numbers	Crisp value	Prior probability
X1	(0.519, 0.612, 0.664, 0.746)	0.635	1.22E−02
X2	(0.449, 0.541, 0.592, 0.672)	0.563	7.68E−03
X3	(0.350, 0.442, 0.484, 0.577)	0.463	3.83E−03
X4	(0.515, 0.606, 0.637, 0.728)	0.621	1.12E−02
X5	(0.279, 0.368, 0.407, 0.497)	0.388	2.09E−03
X6	(0.406, 0.497, 0.538, 0.629)	0.518	5.66E−03
X7	(0.365, 0.456, 0.486, 0.576)	0.471	4.05E−03
X8	(0.249, 0.329, 0.389, 0.479)	0.362	1.67E−03
X9	(0.219, 0.298, 0.357, 0.446)	0.331	1.23E−03
X10	(0.603, 0.697, 0.738, 0.821)	0.714	2.01E−02
X11	(0.217, 0.307, 0.347, 0.438)	0.327	1.19E−03
X12	(0.545, 0.639, 0.680, 0.752)	0.653	1.37E−02
X13	(0.265, 0.345, 0.396, 0.486)	0.374	1.85E−03

Table 9
Prior and posterior probabilities of root nodes.

Node	Prior probability	Posterior probability
X1	1.22E−02	2.59E−02
X2	7.68E−03	1.58E−02
X3	3.83E−03	7.58E−03
X4	1.12E−02	2.42E−02
X5	2.09E−03	4.13E−03
X6	5.66E−03	1.18E−02
X7	4.05E−03	8.24E−03
X8	1.67E−03	3.28E−03
X9	1.23E−03	2.35E−03
X10	2.01E−02	3.22E−02
X11	1.19E−03	2.09E−03
X12	1.37E−02	1.54E−01
X13	1.85E−03	1.98E−02

does not occur, the probability of node M2 reduces to 5.8 %. Besides, if node X2 occurs, the probability of M2 increases to 69 %. If it does not occur, the probability of M2 decreases to 6.2 %. Similarly, an increase in the value of the parent node X3 causes an increase in the child node M2, or a decrease in the value of the parent node X3 causes a decrease in the child node. Axiom 1 test is applied to all child nodes and their parent nodes in the Bayesian network in the paper. According to all the results obtained, the modelled Bayesian network meets the requirements of Axiom 1. For the Axiom 2 test, child node M5 and parent nodes X10 and X11 are chosen as examples, as illustrated in Fig. 5. Gradually increasing the probability of occurrence of parent nodes X10 and X11 leads to a gradual increase in the probability of occurrence of M5, and vice versa. As a result of Axiom 2 tests in the modelled Bayesian network, it was determined that the effect of gradual changes in the probabilities of parent nodes on child nodes is consistent. To verify Axiom 3, we take the intermediate node M3 in Fig. 6 as an example. When X4 is adjusted to 100 %, the probability of M3 increases from 4.1 % to 75.7 %. When the change is fused with X5 adjusted to 100 %, the probability increases to

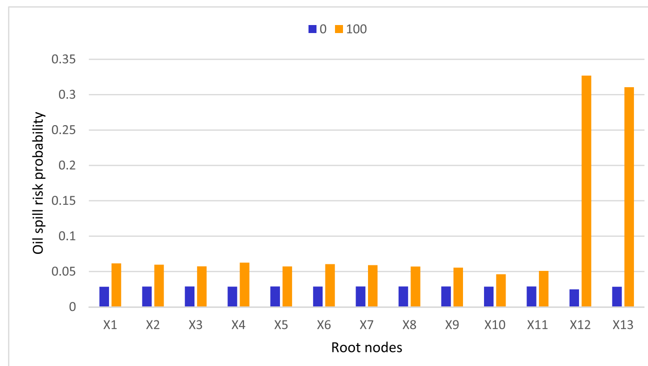

Fig. 4. Sensitivity analysis for root nodes.

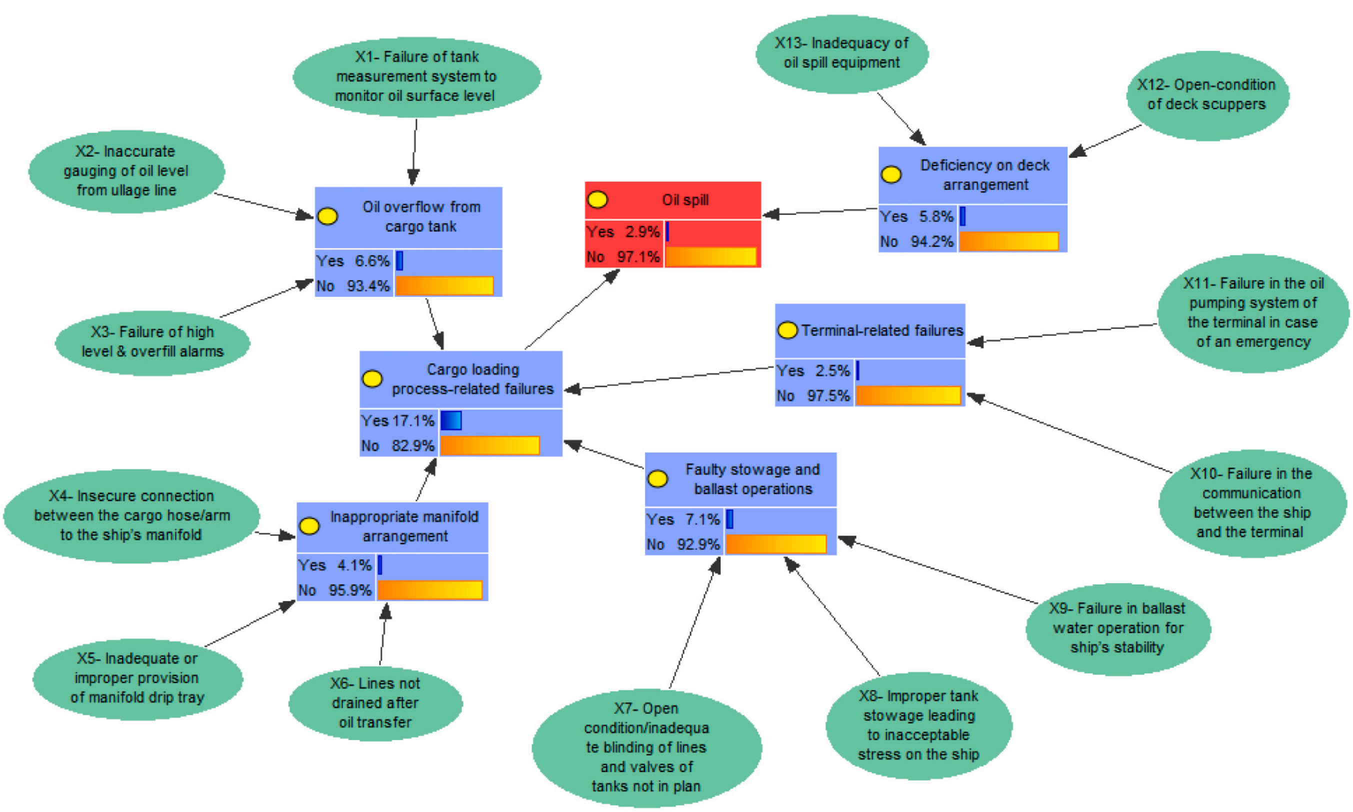

Fig. 3. Causal inference results for oil spill risk during the cargo loading operation.

Table 10
Comparison between prior probabilities with Z-number and without Z-number.

Node	Prior probability with Z-number	Prior probability without Z-number
X1	1.22E−02	1.62E−02
X2	7.68E−03	1.06E−02
X3	3.83E−03	5.00E−03
X4	1.12E−02	1.66E−02
X5	2.09E−03	3.05E−03
X6	5.66E−03	7.87E−03
X7	4.05E−03	5.62E−03
X8	1.67E−03	2.39E−03
X9	1.23E−03	1.79E−03
X10	2.01E−02	2.77E−02
X11	1.19E−03	1.73E−03
X12	1.37E−02	1.76E−02
X13	1.85E−03	2.74E−03

Table 11
Test of Axiom 1 for node M2.

State	Parent nodes	Child node
Yes	Failure of the tank measurement system to monitor the oil surface level (X1)	Oil overflow from the cargo tank (M2)
	Prior probability	0.066
	100 %	0.730
	0 %	0.058
Yes	Inaccurate gauging of oil level from ullage line (X2)	Oil overflow from the cargo tank (M2)
	Prior probability	0.066
	100 %	0.693
	0 %	0.062
Yes	Failure of high level & overfill alarms (X3)	Oil overflow from the cargo tank (M2)
	Prior probability	0.066
	100 %	0.644
	0 %	0.064

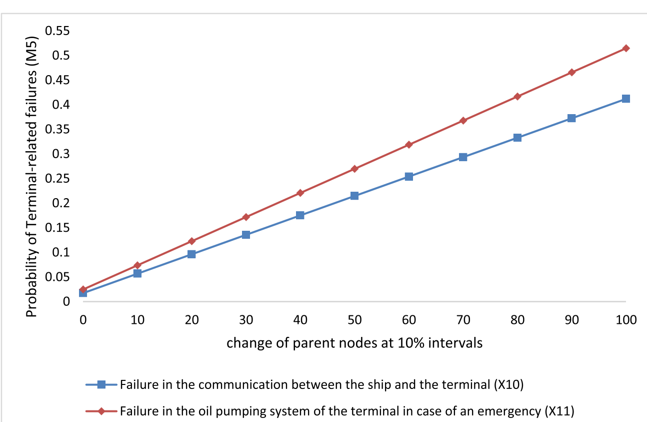

Fig. 5. Test of Axiom 2 for node M5.

95.5 %. Finally, when X6 is adjusted to 100 %, the probability increases to 98.9 %. So Axiom 3 is also validated. Other parent nodes are tested and validated. The results show that the constructed BN model is accurate.

4.4. Findings and discussion

According to Fig. 4, the most critical root nodes are X12, X13, X4, X1 and X6, respectively. X12 is the most critical root node and it represents the: open-condition of deck scuppers. There are scuppers onboard ships to directly discharge the liquids on deck such as rain waters, routine deck cleaning waters etc. However, during cargo operations, the deck scuppers should be clogged. The closed condition of deck suppers is one of the first preventive actions when an overflow from the tanks and a spill occurs. The second critical root node is X13, the inadequacy of oil spill equipment. Adequacy and usability of the oil spill equipment onboard may help to prevent the spill reaches to the marine environment. Air operated diaphragm pump arrangement should be existed onboard, and it should be set to transfer oil to the slop tank, where the spilled oil can be collected safely (ISGOTT, 2020). The third critical root node is X4, the insecure connection between the cargo hose/arm to the ship's manifold. In order to perform a loading operation, the first step is establishing the manifold arrangement. Cargo hoses or arms are connected between the ship's manifold and the terminal's, following that, the crude oil is transferred to the ship. The rate of the cargo transfer can vary according to the loading plan, but it should be noted that the pressure inside the hose or arm can be in high levels. At this point, in case the connection is not well set and secured, the oil can easily spill from the weakest point. Therefore, connection at the manifold area is critical for proper and clean oil transfer. Both ship and shore responsible personnel should check the condition of cargo hoses or arms from the aspects of size, gaskets, material etc. (ISGOTT, 2020; Sezer et al., 2023). X1 is the fourth most critical root node, the failure of the tank measurement system to monitor the oil surface level. X1 is categorized as a root cause under the intermediate node M2, the issue of oil overflow from the cargo tank. It is not mostly possible for the crew to see inside the cargo tanks and understand the correct level of the oil. Therefore, the interior of the cargo tanks is followed by fixed monitoring systems that use sensors, and they send the information to computers in the cargo control room. Their usage is essential for the ship officers particularly when loading the tank around 90 % filling levels. Those systems should be checked before cargo operations and their software should be updated. The other significant root cause is X6, which is the lines not drained after oil transfer. At the end of the loading; the cargo lines should be drained into the relevant tank so that the cargo expands as a result of heating, damaging the line and leakage is prevented. Sufficient volume should be left for the amount to be drained in the final tank (ISGOTT, 2020).

Moreover, according to Table 9, root nodes X12, X10, X1, X4, and X13 have a higher posterior probability, respectively. These root nodes require extra attention to prevent oil spills. Root nodes with the highest posterior probability and the most critical root nodes are almost identical. In addition, X10, failure in the communication between the ship and the terminal has the second highest posterior probability value. The ship officers need to contact terminal personnel to inform the operational conditions such as cargo transition, rate monitoring, the filling level of tanks, or tank changeovers. Besides, the terminal is also responsible for conducting a smooth communication especially when loading a ship, since loading is performed via the terminal's pumping systems. In case of an emergency, effective communication is crucial between the ship and the terminal as the terminal may stop the loading immediately to avoid oil spills.

5. Conclusion

Crude oil transportation via seaways is a significant part of the global trade for energy provision. A large quantity of crude oil is handled every day and carried via tanker vessels. Although it is routine work in maritime transportation, it poses risks for human life, property and the marine environment. This paper focuses on the oil spill risk during crude oil cargo operation onboard tanker ships, since the oil spill can lead to acute environmental hazards and damage coastal habitats. Besides, those effects may last over many years, adversely affecting other businesses related to coastal activities. The research of crude oil loading operation should be taken into consideration by both the ship crew and the terminal as it involves different risky parameters that can lead to oil spillage. To perform a quantitative risk analysis for oil spill incidents, a robust methodological combination is introduced. The Bayesian Network method is used with the support of improved Z-numbers and

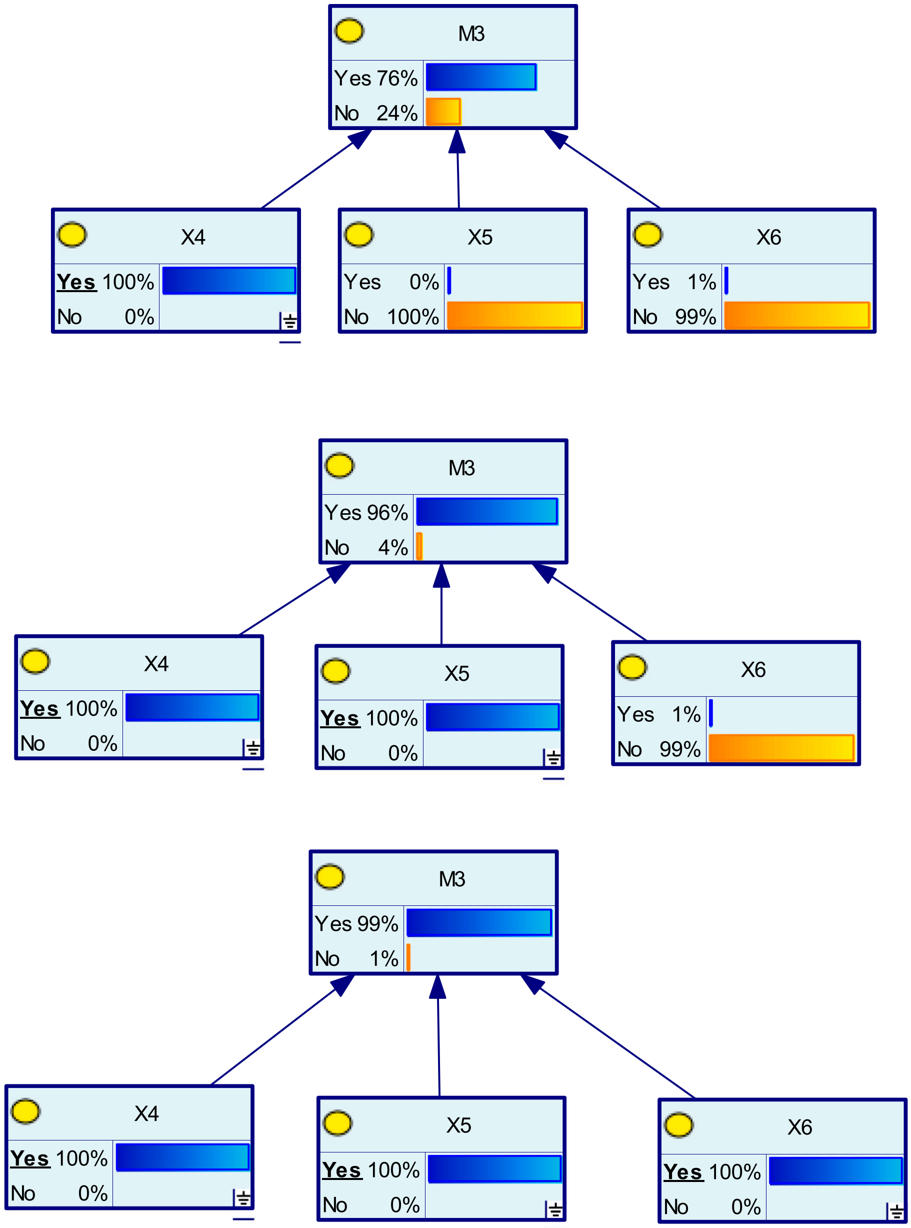

Fig. 6. Test of Axiom 3 for intermediate node M3.

fuzzy logic theory. Bayesian Networks helped to establish the cause and effect network between the variables in a systematic way, while the improved Z-numbers and fuzzy logic are utilized to deal with the uncertainty arising in the expert judgment step.

According to the findings, the occurrence probability of the oil spill risk on the crude oil tanker ship is found 2.90E−02 by evaluating the cargo loading operation. The posterior probabilities of the root nodes showed that the highest ranked roots are X12 (Open-condition of deck scuppers), X10 (Failure in the communication between the ship and the terminal), X1 (Failure of the tank measurement system to monitor the oil surface level), X4 (Insecure connection between the cargo hose/arm to the ship's manifold), and X13 (Inadequacy of oil spill equipment). Additionally, according to sensitivity analysis, the most critical root nodes are X12 (Open-condition of deck scuppers), X13 (Inadequacy of oil spill equipment), X4 (Insecure connection between the cargo hose/arm to the ship's manifold), X1 (Failure of the tank measurement system to monitor the oil surface level) and X6 (Lines not drained after oil transfer). These variables are considered significant root causes that may lead to oil spill incident and requires attention by the responsible personnel. The paper also assessed the highest ranked roots with appropriate safety actions. Therefore, the research results are expected to contribute to the safety of tanker operations. It may provide useful perspectives for the ship officers, terminal managers, company safety and environmental departments for the risk assessment and decision-making progresses to improve operational and environmental safety.

CRediT authorship contribution statement

Sukru Ilke Sezer: Writing – original draft, Methodology, Data curation, Visualization, Formal analysis. **Gizem Elidolu:** Writing – original draft, Visualization, Investigation, Data curation, Formal analysis. **Emre Akyuz:** Writing – original draft, Writing – review & editing, Conceptualization, Supervision. **Ozcan Arslan:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A

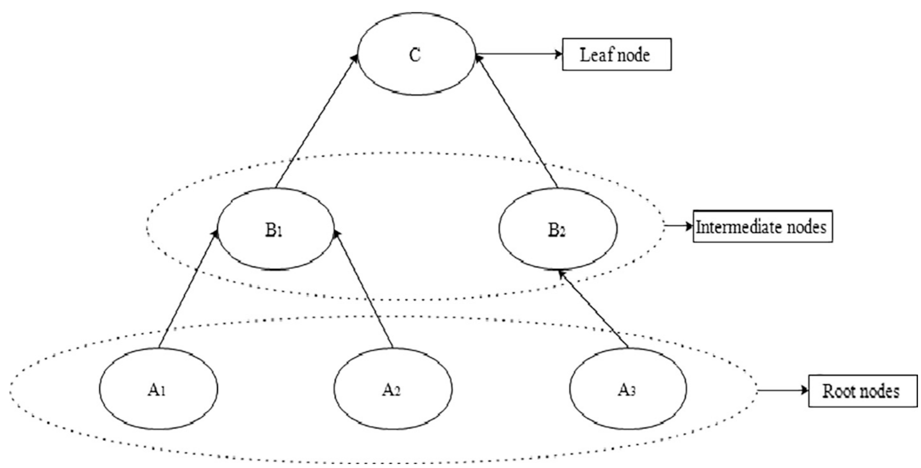

Fig. A.1. Simple Bayesian network model.

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