Risk Analysis of Petroleum Transportation using Fuzzy Rule-Based Bayesian Reasoning

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***Abstract*—Petroleum Transportation Systems (PTSs) play a critical role in the movement of crude oil from its production sites to end users. Such systems are complex because they often operate in a dynamic environment. Safe operations of the key components in PTSs such as port and shipping are vital for the success of the systems. Risk assessment is a powerful tool to ensure the safe transportation of crude oil. This paper applies a mathematical model to identify and evaluate the operational hazards associated with PTSs, by incorporating a Fuzzy Rule-Based (FRB) method with Bayesian Networks (BNs). Its novelty lies in the realisation of risk analysis and prioritisation of the hazards in PTSs when historical failure data is not available. This hybrid model is capable of assisting decision-makers in measuring and improving the PTSs' safety, and dealing with the inherent uncertainties in risk data.**

***Keywords*— Bayesian belief network; fuzzy set theory; maritime risk; maritime transport; petroleum transportation**

I. INTRODUCTION

Petroleum supply chains have a strategic impact on global, national, and local economy. Various operational activities need to be undertaken properly at different stages within supply chains. Such activities involve exploration and production, the conversion of crude oil to refined products, and storage intended for reaching a desired market. These operational activities are complicated in nature and render petroleum supply chains highly risky.

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Petroleum Transportation Systems **(**PTSs) play a vital role in the flow of crude oil. The PTSs enable the movement of crude and/or refined products from starting point (i.e. production sites or storage tanks) to their final destinations, via land and/or sea. During the crude oil journey through the Petroleum Supply Chain (PSC), multiple systems are involved, including nodes such as ports and depots and links like pipelines, tankers, and rail systems (Kazemi and Szmerekovsky, 2015). To ensure the smooth flow of the products within the system, tankers and pipelines are the two most commonly used transportation modes (Pootakham and Kumar, 2010; Herrán, *et al*., 2010). While ports act as the connecting points between the transportation modes, pipelines and tankers are used for inland and sea transportation, respectively.

The U.S. Energy Information Administration (2014) stated that, in 2013, 56.5 million barrels of oil per day (bbl/d) were transported by sea. In other words, about 63% of total world crude oil production (i.e. 90.1 million bbl/d) was moved through PTSs. In addition, the U.S. Energy Information Administration (2017) stated that, 96.7 million bbl/d was the total world production of crude oil, where 58.9 million bbl/d (i.e. about 61% of the total production) was carried via sea transportation systems in 2015. It highlighted the rapid growth in crude oil production and its high demand market. The great demand on this critical product led to an increase in the quantity of crude oil that was transported within the PTSs (i.e. 2.4 million bbl/d increase in crude oil movement). For that reason, production and consumption of crude oil is highly associated with economic development. Therefore, ensuring PTS operation in a safe condition, is a significant element for sustaining global and local industries. If an unwanted event strikes any of the systems within the PTSs, its consequences will affect the overall petroleum industry. Therefore, it is vital to identify and assess the hazards affecting PTSs, and improve the overall safety and reliability of the systems.

The aim of this paper is to apply an advanced risk assessment technique for evaluating the risk of PTSs' operational hazards. It provides decision-makers with an advanced risk analysis tool capable of dealing with the issues such as lack of existing data and high level of uncertainty in PTSs operational assessment, which make it impossible to employ classical risk analysis techniques (e.g. probabilistic risk analysis). In this paper, an established Fuzzy Rule-Based Bayesian Networks (FRBN) methodology is applied in the new context of PTSs. The Bayesian Network (BN) mechanism is used to synthesize all *IF-THEN* rules with belief structures, and to detect the failure priority values of PTSs hazards. This assessment model is capable of assisting decision-makers to understand the PTSs' safety, in order to enhance the effectiveness of their operations. To accomplish this aim, the paper starts with the identification of the research gap of previous PTSs studies in Section II. It is followed by an overview analysis of Failure Mode and Effects Analysis (FMEA) and BN methods. Section III includes a step-by-step description of the methodology that has been used for evaluating and prioritising the risk levels of the PTSs' operational hazards. The proposed methodology is demonstrated by investigating a real PTS case study in Section IV. Finally, the conclusion, with the discussion of future work, is presented in Section V.

II. Literature Review

A. Risk Assessment of Petroleum Transport

The nature of a PSC requires extreme priority to be placed on safety. Risk management plays a critical role in ensuring the transportation system resilience in the context of PSCs. Recent studies highlight the importance of the PTSs' safety, during the transportation of crude oil. A careful literature review has revealed that several studies have been conducted on operational risk and reliability relating to PTSs, but most have the analysis conducted from a segment level a for single system (i.e. port, ship, or pipeline system), instead of a systematic perspective. For instance, Mokhtari, *et al*. (2011) proposed a step-by-step fuzzy risk analysis in order to evaluate the overall risk level of petroleum sea ports and terminals. Pak, *et al*., (2015) used a fuzzy Analytical Hierarchy Process (AHP) technique for evaluating the factors that influence ports' safety from ship captains' perspectives. Rao and Raghavan (1995) proposed a cause-consequence analysis to detect hazard events associated with ports installation. Yuhua and Datao (2005) developed a risk-based modelling technique using fuzzy Fault Tree Analysis (FTA) for analysing the failures associated with oil and gas transmission pipelines. Shahriar, *et al*. (2012) proposed the combination of a bow-tie method and fuzzy logic to overcome the vagueness of oil and gas pipelines. Uğurlu, *et al*. (2015) used FTA for analysing the collision and grounding of oil tanker accidents depending on the data collected from theGlobal Integrated Shipping Information System (GISIS) from 1998 to 2010. Martins and Maturana (2013), proposed a risk assessment technique using Bayesian Belief Networks (BBNs) while investigating human elements during oil tanker operations. Further research such as Mokhtari, *et al*. (2012) and Ronza, *et al*. (2006) focused on the local level of the petroleum ports, while studies such as Restrepo, *et al*. (2015) and Trucco, *et al*. (2008) focused on the tankers or pipeline systems. Within the environment of supply chains, optimal risk controls at segment/local levels of a single system without considering other involved operational systems might not necessarily confirm the highest safety at the system level. It consequently reveals a research area needed to be fulfilled.

The connections within PTSs form a complex system. This is demonstrated by the fact that there are multiple sub-systems (i.e. ports, tankers and pipelines) engaged within its operations. Therefore, in this paper, each of these three key sub-systems is further investigated, to detect their individual hazards on the same measurement plate. A failure in the PTSs is not necessarily due to the occurrence of a whole series of errors. Nevertheless, a single failure or mistake might be the cause leading to the system's failure. Through carrying out a careful identification process (i.e. literature review), the hazards within petroleum ports and transportation modes (i.e. ship and pipeline), have been selected. The highlighted hazards have been further verified by domain experts in several meetings that took place in 2015 and 2016.

B. Fuzzy Rule-Based Bayesian Reasoning

FMEA has been defined as a step-by-step procedure for evaluating safety and reliability of failure modes and effects (Liu, *et al*. 2013). FMEA is probably one of the most common and widely used techniques in safety and reliability analysis. In the mid 20 century, the FMEA approach was firstly introduced to the aerospace industry. Its popularity has been spread across different industries, such as aerospace, automotive, nuclear, and medical to improve their production safety and reliability (Sankar and Prabju, 2001; Aldridge, *et al.*, 1991; Russomanno, *et al.*, 1992). In the traditional FMEA, the level of safety of each failure mode is determined by three parameters; Likelihood (L_k), Consequence (C_s) and Probability (P_b) (Yang *et al*., 2008).

Nevertheless, the traditional FMEA method suffered from some drawbacks that have been criticised by numerous scholars, such as the problem associated with the Risk Priority Number (RPN) (Wang, *et al*., 2009; Chin, *et al*., 2009). To overcome these weaknesses, and improve the FMEA performance, uncertainty based techniques, such as artificial neural networks (Keskin and Özkan, 2009), Dempster-Shafer theory (Liu, *et al*., 2005), fuzzy set theory (Xu, *et al*., 2002), grey theory (Pillay and Wang, 2003), evidential reasoning (Yang, 2001), and Monte Carlo simulation (Bevilacqua, *et al*., 2000) have been proposed in the literature. In addition, Emovon, *et al*. (2015) used VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique and FMEA in developing an assessment model to prioritize the failures in a medical system. Puente, *et al.* (2002) presented an improved qualitative rule-based method in FMEA to overcome the traditional FMEA problems for risk ranking. Guimarães and Lapa (2007) proposed fuzzy rule-based in FMEA in nuclear engineering in addressing the questions related to the traditional RPN while prioritizing the failures. Liu, *et al.* (2014) combined interval 2-tuple linguistic variables with grey relational analysis to improve the effectiveness of the traditional FMEA in medical services. Jiang, *et al.* (2017) developed an advance risk ranking method based on fuzzy evidential theory in a Micro-Electro-Mechanical System (MEMS). Tazi, *et al.* (2017) integrated cost factors to traditional FMEA to improve system design reliability of wind turbine systems.

FRBN was developed by Yang, *et al*. (2008) to overcome the traditional FMEA drawbacks. This advanced hybrid technique was established in order to identify failure priority values, by using the mechanism of Bayesian Reasoning to conduct Fuzzy Rule-Based (FRB) risk inference (Alyami, et al., 2014; Yang et al., 2015). The FRBN improves the accuracy of failure assessment while not significantly increasing complication of the relevant calculation (Yang, et al., 2008). In other words, it increases the result accuracy compared to the traditional FMEA approach without compromising the visibility and easiness of the traditional FEMA". A BN method was developed in the 1970s, based on the marriage of the basic Bayesian theory and graphical networking techniques. A BN is a graphical model that provides a decision-support framework for problems involving uncertainty, complexity and probabilistic reasoning (Nadkarni and Shenoy, 2001; Ben-Gal, 2007). In addition, a BN demonstrates the fundamental concept of probabilistic graphical models, or probabilistic networks. Eleye-Datubo, *et al.* (2006) and Khakzad, *et al.* (2013) highlighted that directed graph and Conditional Probability Tables (CPTs), which play critical rules in identifying the relationship between the modelled variables, are the two main components of any BN. For dealing with uncertain knowledge, the technique has been extensively and successfully applied in various fields such as medical (Spiegelhalter, *et al.*, 2013), transportation (Li, *et al.*, 2014), engineering (Feng, *et al.*, 2014), management (Rahman, *et al.*, 2015), and many others. Within the petroleum industry, Cai, *et al.* (2013) used BN to measure the human factors risk in offshore systems. Ren, *et al.* (2008) integrated Swiss Cheese model and BN to evaluate offshore safety. A BN model was developed by Antão, *et al.* (2009) for maritime shipping accidents based on the Portuguese Maritime Authority database. Trucco, *et al.* (2008) proposed a BN to model the maritime transportation system by integrating human and organizational factors into risk analysis.

The beauty of BN lies in its ability in providing a powerful analysis tool due to its capability in capturing non-linear causal relationships (Yang, *et al.*, 2008; Alyami *et al.*, 2014). It can be used to undertake two directional forward risk prediction and backward risk diagnosis (Yang *et al.*, 2009a; Hu *et al.*, 2008). The traditional BN graphical structure consists of: 1) a set of nodes, representing variables connected by 2) a set of edges representing the dependence between these variables (Trucco, *et al.*, 2008; Riahi, *et al.*, 2008). The direction of the edge represents the relationship of each node to another node (Alyami, *et al*., 2014). The edge starts from a parent node and ends with an arrowhead pointing to a child node. If a parent node has no its own parents, it is also called a "root" node. Nodes without child nodes are called "leaf" nodes (Trucco, *et al.*, 2008; Vinnem, *et al.*, 2012).

III. METHODOLOGY

The nature of PTSs makes the system operates in unsafe and unstable environment. Hence, subjective data based on expert judgements are used to complement the incompleteness of objective data. In this paper, an assessing model is constructed and an amalgamation of FRB in FMEA and BN is employed for evaluating the risk of the hazards associated with the PTSs. A FRB is employed to model the conditional statements as well as to incorporate the overall knowledge. In addition, a BN is used to provide a decision-supporting framework, for the evaluation of the hazards associated with the petroleum ports, ships, and pipeline systems operations within the PTSs, through the use of probabilistic reasoning. For analysing the PTSs' operational hazards, a step-by-step analysis procedure is presented in Fig. 1 and described as follows:

- Step 1. Identify the PTSs hazards.
- Step 2. Establish fuzzy IF-THEN rules within FMEA.
- Step 3. Develop a BN model and aggregate the rules by using BN mechanism.
- Step 4. Prioritise the PTSs' hazards.
- Step 5. Sensitivity analysis.

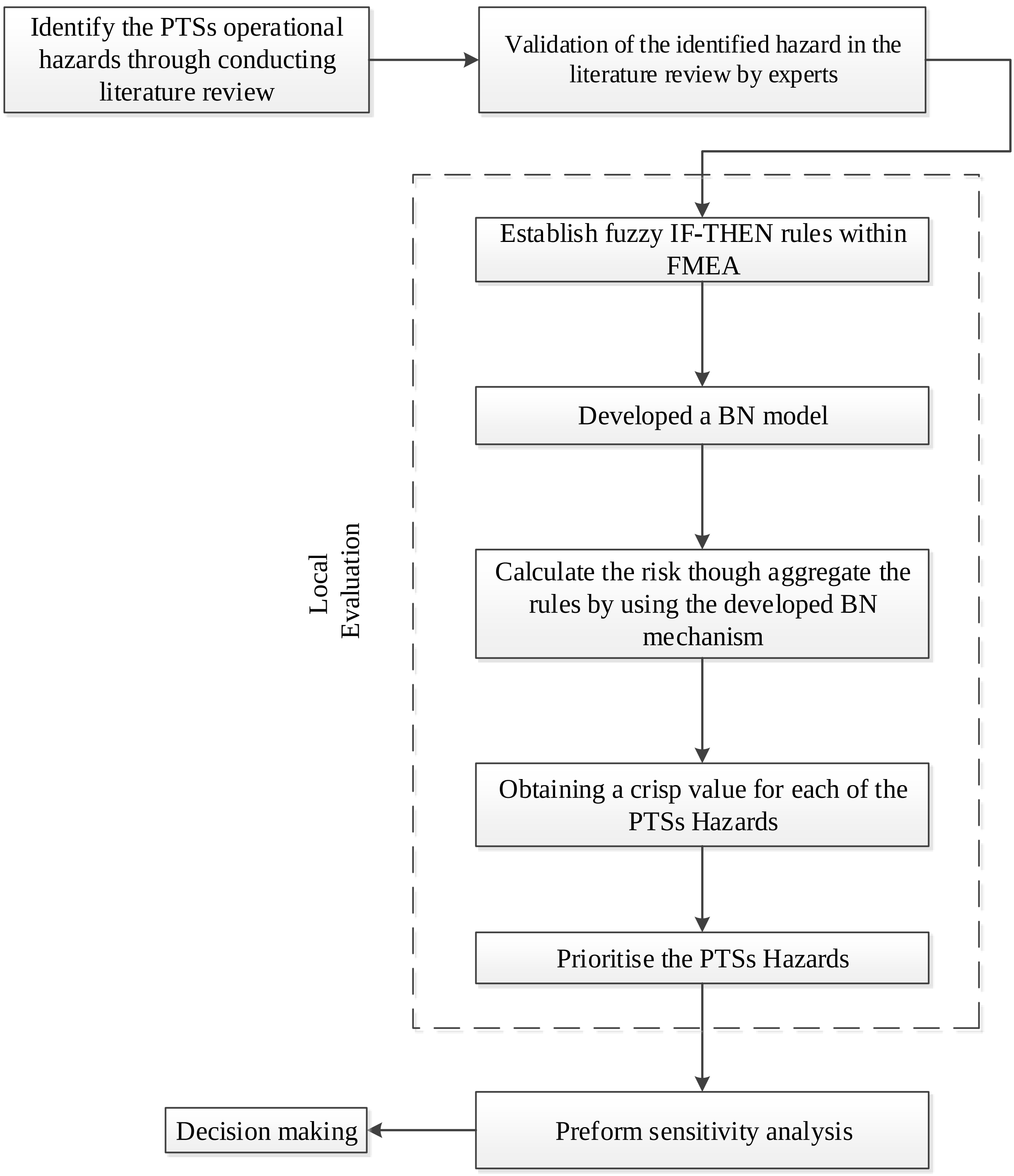

Fig. 1. The PTSs' assessment model flow chart.

A. Identify the PTSs Hazards (Step 1)

This step identifies the Hazards (Hs) related to PTSs. This identification process provides decision-makers with a clear picture of the hazards associated with the working environment to ensure the safety of the system. The PTSs consist of two sub-systems: ports and transportation modes. Tankers and pipelines are the two major transportation modes within this system (see Fig.2).

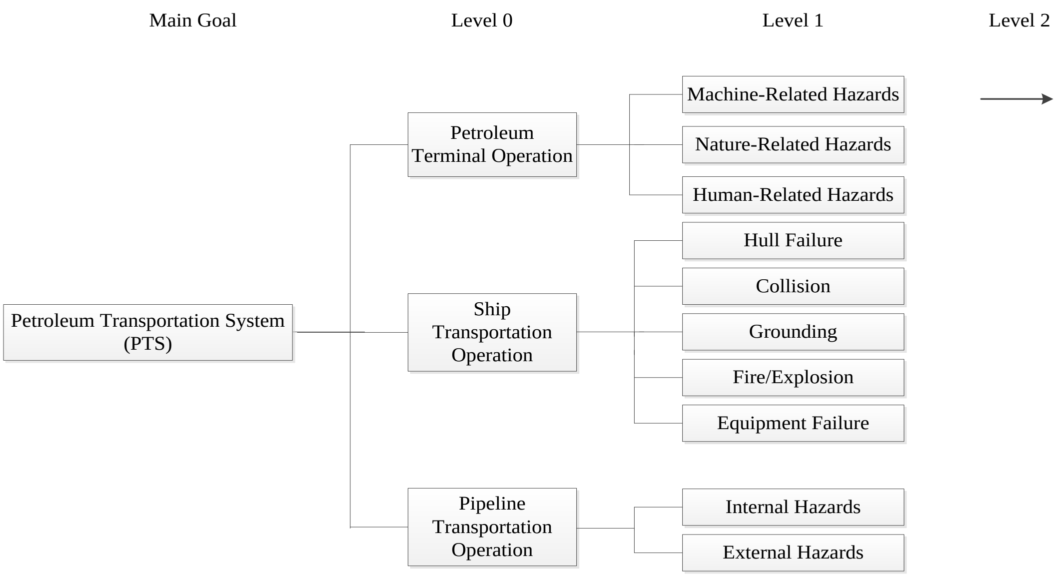

Fig. 2. Main hierarchical structure of the hazards in the PTSs.

Due to the complexity of the process of identifying the hazards in PTSs, a cause and effect analysis technique (Chang and Lin, 2006) has been used in this study. An extensive literature review was conducted to identify the hazards that influence the safe operations of crude oil terminals, pipelines, and ships. (Ceyhun, 2014; Vinnem *et al.*, 2012; Ismail and Karim, 2013; Cai *et al.*, 2013). Furthermore, through conducting a brainstorming technique, consultation with domain experts has been carried out to determine whether the identified hazards exist in the investigated PTSs operations or not. To obtain better results in identifying PTSs hazards within these meetings, what-if analysis, which is a brainstorming approach, is used. What-if analysis is a popular technique and possibly one of the oldest hazard identification methods; it involves simply asking a series of questions that begin with 'what if' (Khan and Abbasi, 1998; Kavianian *et al.*, 1992; Golfarelli and Rizzi, 2010). These consultation meetings took place in November 2015 in the UK and in January 2016 in Saudi Arabia with nineteen petroleum/refined petroleum products' terminal managers, pipeline and ship operators, and scholars. Within these meetings, the researcher asked the experts a number of questions start with 'what if' (i.e. What if the communication system Breakdown during operation?) Consequently, the hazards that are most influential on the PTSs' safety are listed in Table. I. The index of each hazard is expressed by the combination of the number of hazards and the symbols of the sub-systems. For instance, the hazard in the first row and first column, company policies is indexed as Po-H1.

Table I: Hazards associated with the operation of each system within the PTSs

	Port Transportation System	**Ship Transportation System**	**Pipeline Transportation System**
H 1	Company Policies	Ship Collision due to Main Engine Failure	Sabotage
H 2	Company Standards	Ship Collision due to Bridge Navigation Equipment Failure	Workers Actions
H 3	Management Procedure	Ship Collision due to Communication System Failure	Weather Condition
H 4	Inattention	Ship Collision due to Wrong use of Navigation Equipment	Geological Hazards
H 5	Neglect	Ship Collision due to Lack of Communication	Material Failure

H 6	Fatigue	Ship Collision due to Failure to Follow Operational Procedure	Construction Failure
H 7	Skills	Action To Avoid Collision	Maintenance Failure
H 8	Overfill	Ship Collision due to Human Inattention	Failure to Follow Procedure
H 9	SOPs (Standard Operating Procedures) Not Followed	Ship Collision due to Human Neglect	Internal Corrosion
H 10	Overpressure	Ship Collision due to Human Fatigue	External Corrosion
H 11	Release From Loading Arm/SBM	Ship Collision due to Human Skills	
H 12	Understaffing	Ship Collision due to Weather Condition	
H 13	Breakdown of Communication	Ship Collision due to Third Party Activity	
H 14	Communication Misunderstanding	Ship Grounding due to Main Engine Failure	
H 15	Wrong Signals	Ship Grounding due to Communication System Failure	
H 16	Procedural Failure	Ship Grounding due to Bridge Navigation Equipment Failure	
H 17	Collision between Ship and Other Ship/Berth	Ship Grounding due to Wrong use of Navigation Equipment	
H 18	Lack of Tools/Spare Parts	Ship Grounding due to Lack of Communication	
H 19	Inappropriate maintenance practice	Ship Grounding due to Failure to Follow Operational Procedure	
H 20	Use of Inappropriate Tools/Spare Parts	Ship Grounding due to Rout Selection	
H 21	Maintenance Omission	Ship Grounding due to Using Inappropriate Chart	
H 22	Lack of Communication System	Ship Grounding due to Human Inattention	
H 23	Lack of Lighting System	Ship Grounding due to Human Neglect	
H 24	Lack of Movable Facilities	Ship Grounding due to Human Fatigue	
H 25	A/C System Failure	Ship Grounding due to Human Skills	
H 26	Control System Failure	Ship Grounding due to Weather Condition	
H 27	Instrument Failure	Ship Grounding due to Third Party Activity	
H 28	Valve Failure	Ship Grounding due to Water Depth	
H 29	Hose/Pump Failure	Hull Failure due to Construction Damage	
H 30	Gasket Failure	Hull Failure due to Hull Corrosion	
H 31	Pipeline Failure	Hull Failure due to Maintenance Failure	
H 32	Loading Arm/SBM Failure	Hull Failure due to Stowage Planning Failure	
H 33	Power Failure	Hull Failure due to Collision	
H 34	Cathodic Protection Failure	Hull Failure due to Grounding	
H 35	Heavy Rainfall	Fire/Explosion due to Human Inattention	

H 36	Flood	Fire/Explosion due to Human Neglect
H 37	Snow	Fire/Explosion due to Human Skills
H 38	Hurricane	Fire/Explosion due to Inert Gas/Ventilation System Failure
H 39	Tornadoes	Fire/Explosion due to Electric Failure
H 40	Lightning	Fire/Explosion due to Pumping Room Failure
H 41	Earthquake	Fire/Explosion due to Main Engine Failure
H 42	Tsunami	Fire/Explosion due to Heating system Failure
H 43		Fire/Explosion due to Spread of Fire From Other Object
H 44		Fire/Explosion due to Sabotage
H 45		Fire/Explosion due to Weather Condition
H 46		Equipment Failure due to Pipe Failure
H 47		Equipment Failure due to Valve Failure
H 48		Equipment Failure due to Pump Failure
H 49		Equipment Failure due to Tank Gauging System
H 50		Equipment Failure due to Manifold Failure
H 51		Equipment Failure due to Power Failure
H 52		Equipment Failure due to Heating System Failure
H 53		Equipment Failure due to Loading Computer
H 54		Equipment Failure due to Maintenance Error
H 55		Equipment Failure due to Maintenance Omission
H 56		Equipment Failure due to Lack of Communication
H 57		Equipment Failure due to Procedural Failure
H 58		Equipment Failure due to Human Inattention
H 59		Equipment Failure due to Human Neglect
H 60		Equipment Failure due to Human Fatigue
H 61		Equipment Failure due to Human Skills

B. Establish Fuzzy IF-THEN Rules within FMEA (Step 2)

Three risk parameters are employed to analyse failure modes in the traditional FMEA. For constructing a fuzzy *IF-THEN* rule with a belief structure for PTSs, the occurrence probability of a risk event during the process of oil transport (P_l), consequence severity that the risk event causes when it occurs (S_c), and probability that the risk event cannot be detected before it occurs (D_p) are defined as FMEA factors. P_l, S_c and D_p are the three risk parameters that are used in the IF part. However, in the THEN part, the risk level (R) is presented. Very High, High, Medium, Low, and Very Low are the set of linguistic variables used to describe P_l, S_c, D_p and R (Mokhtari, *et al*., 2012; Pillay and Wang, 2003; Sii, *et al*., 2001). These grades describe the linguistic variables of each attribute associated with the PTSs' Hs. Through considering experts' judgements, the degree of each parameter is valued with regard to each identified hazard. Tables II, III and IV illustrate the attributes' linguistic variables, where each parameter is defined based on knowledge accrued from past events.

Table II: Linguistic grades for the occurrence probability parameter for each H in the IF part (Pillay and Wang, 2003; Sii, *et al*., 2001; Liu, *et al*., 2011; Yang, *et al*., 2008; Zaman, *et al*., 2014)

The H P_l during oil transportation process	**Description**
Very Low	The probability of occurrence is unlikely to occur but possible
Low	The probability of occurrence is likely once per year
Medium	The probability of occurrence is likely once per quarter
High	The probability of occurrence is likely once per month
Very High	The probability of occurrence is expected once per month

Table III: Linguistic grades for the consequence severity parameter for each H in the IF part (Pillay and Wang, 2003; Sii, *et al*., 2001; Liu, *et al*., 2011; Yang, *et al*., 2008; Zaman, *et al*., 2014)

The H S_c during oil transportation process	**Description**
Very Low	No injury involved and negligible damage to the system; no damage to the environment.
Low	Minor medical treatment; slight equipment or system damage but fully functional and serviceable; minor environmental damage
Medium	Minor injury; moderate incapacity of systems, equipment or facilities that disrupts operations; moderate damage to the environment
High	Permanent total disability; damage to major facilities; severe environmental damage
Very High	Death; loss of major facilities; major environmental damage

Table IV: Linguistic grades for the undetectable probability parameter for each H in the IF part (Pillay and Wang, 2003; Sii, *et al*., 2001; Liu, *et al*., 2011; Yang, *et al*., 2008; Zaman, *et al*., 2014)

The H D_p not being detectable before it occurs	**Description**
Very Low	Possible to be detected without inspections or maintenance
Low	Possible to be detected through regular inspections or maintenance
Medium	Possible to be detected through intensive inspections or maintenance
High	Difficult to be detected through intensive or regular inspections or maintenance
Very High	Impossible to be detected through intensive or regular inspections or maintenance

In the FRB, a belief structure is utilised to model the THEN part in the IF-THEN rule. For example (Alyami, *et al*., 2014):

- Rule 1: *IF P_l is Very High, S_c is Very High and D_p is Very High, THEN R is Very High with 100%, High with 0%, Medium with 0%, Low with 0% and Very Low with 0%.*
- Rule 2: *IF P_l is Very High, S_c is Very High and D_p is High, THEN R is Very High with 67%, High with 33%, Medium with 0%, Low with 0% and Very Low with 0%.*
- Rule 3: *IF P_l is Very High, S_c is Very High and D_p is Medium, THEN R is Very High with 67%, High with 0%, Medium with 33%, Low with 0% and Very Low with 0%.*
- Rule 4: *IF P_l is Very High, S_c is Very High and D_p is Low, THEN R_s is Very High with 67%, High with 0%, Medium with 0%, Low with 33% and Very Low with 0%.*

The proportion method has been used to assign belief degrees in the THEN part, for each of the linguistic variables in the above four rules (Alyami, *et al*., 2014). To simplify this, the risk factors that obtain the same grade in the IF part, are divided by the total number of parameters. To rationalise the assignment of the degree of belief of a certain grade in the THEN part for each rule, the following equation is used:

$$D(x) = \frac{\sum_{i=1}^{n} a_i(x)}{n} \tag{1}$$

where $D(x)$ is the belief degree assigned to Very High, High, Medium, Low, or Very Low in the THEN part, n represents the number of factors in the IF part, and $a_i(x)$ describes the grades of a specific linguistic variable of each attribute associated with a targeted Hs. For example, in Rule 1, three risk factors are assigned the Very High grade in the IF part. Therefore, the belief degree for Very High in the THEN part is calculated as 100% (3/3 = 100%). Conversely, two risk parameters have the Very High grade and one gets the High grade in the IF part in Rule 2. Therefore, the belief degrees belonging to Very High and High in the THEN part are 67% (2/3 = 67%) and 33% (1/3 = 33%), respectively. 125 rules (5 × 5 × 5) with their belief degrees are established (Alyami, *et al*., 2014) (see Table V).

C. Develop a BN Model and Aggregate the Rules by Using BN (Steps 3 and 4)

Traditional fuzzy rule aggregation techniques such as max-min operation can cause loss of information in the rule combination process. Other fuzzy rule aggregation methods such as Technique for Order of Preference by Similarity to Ideal Solutions (TOPSIS) and VIKOR have the advantages in ranking failures, but suffer in expressing the riskiness of each failure (Emovon, *et al*. 2015; Song, *et al*. 2013). Evidential Reasoning (ER), addressing the above concerns, involves very complex calculation formulas that are not friendly to mathematically unsophisticated users (John, *et al*., 2014). BN is capable to confirm the relationship between the Hs and the established FRB with belief structure in FMEA to detect failures riskiness (Yang, *et al*., 2008). In this regards, a BN model is developed to rank the identified PTSs' hazards in terms of their risk levels. BN is performed to build a qualitative network capable of representing all the Hs and their dependencies (i.e. the three risk parameters).

To aggregate the rules using a BN, the developed rules should first be presented in a conditional probability form. For example, Rule 2 in Table V is presented as follows:

R2: *IF Very High (P_1), Very High (S_1) and High (D_2), THEN {(0.67, Very High (R_1)), (0.33, High (R_2)), (0, Medium (R_3)), (0, Low (R_4)), (0, Very Low (R_5)),}.*

The conditional probability of Rule 2 can be expressed as follows:

Given P_1, S_1 and D_2, the probability of R_h (h = 1,…,5) is (0.67, 0.33, 0, 0, 0) or

$$\mathrm{P}(R_i | P_1, S_1, D_2) = (0.67, 0.33, 0, 0, 0) \tag{2}$$

where " | " symbolises conditional probability.

The established IF-THEN rules within FMEA can be modelled and transferred by using the BN technique in four nodes. P_l, S_c and D_p represent the parent nodes of each H. These three parent nodes are connected to an H (Node R_h). By converting the overall rule base into a customized BN model, the marginal probability of the H (i.e. child node) can be computed, through simplifying the risk inference mechanism of the rule-base failure criticality evaluation. To marginalise Node R_h, the needed conditional probability table $\mathrm{P}(R_h|P_l, S_c, D_p)$, can be obtain by using Eq. 2 and Table V, which symbolises a 5 × 5 × 5 × 5 table combination, having the values $\mathrm{P}(R_h|P_l, S_c, D_p)$ ($h, l, c, p = 1,…,5$) (Yang *et al.*, 2008).

Table V: The established IF-THEN rules with belief structure for PTSs risk evaluation

Rule No	**Risk Parameters in the IF Part**			**Belief Degree in the THEN Part**				
	P_l	S_c	D_p	VH	H	M	L	VL
1	VH(P_1)	VH(S_1)	VH(D_1)	1	0	0	0	0
2	VH(P_1)	VH(S_1)	H(D_2)	0.67	0.33	0	0	0
3	VH(P_1)	VH(S_1)	M(D_3)	0.67	0	0.33	0	0
4	VH(P_1)	VH(S_1)	L(D_4)	0.67	0	0	0.33	0
5	VH(P_1)	VH(S_1)	VL(D_5)	0.67	0	0	0	0.33
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....	....	....	....	....	....	....	....	....
121	VL(P_5)	VL(S_5)	VH(D_1)	0.33	0	0	0	0.67
122	VL(P_5)	VL(S_5)	H(D_2)	0	0.33	0	0	0.67
123	VL(P_5)	VL(S_5)	M(D_3)	0	0	0.33	0	0.67
124	VL(P_5)	VL(S_5)	L(D_4)	0	0	0	0.33	0.67
125	VL(P_5)	VL(S_5)	VL(D_5)	0	0	0	0	1

Each of the identified PTSs' Hs can be evaluated by using experts' judgements, through considering the three risk factors (i.e. P_l, S_c and D_p) and their related defined linguistic grades. Moreover, for assigning the belief degree of the linguistic grades of each individual factor, the averaging technique is used to combine the judgements from multiple experts for calculating the prior probabilities (i.e. $\mathrm{P}(P_l)$, $\mathrm{P}(S_c)$ and $\mathrm{P}(D_p)$) of the three parent nodes, P_l, S_c and D_p. As a result, the marginal probability of each H (R_h) can be calculated as follows (Yang, *et al.*, 2008)

$$\mathrm{P}(R_h) = \sum_{l=1}^{5}\sum_{c=1}^{5}\sum_{p=1}^{5}\mathrm{P}(R_h | P_l, S_c, D_p)\mathrm{P}(P_l)\mathrm{P}(S_c)\mathrm{P}(D_p) \quad (h = 1,\dots,5) \tag{3}$$

D. Prioritise the PTSs' Hazards (Step 5)

In the FRBN model, the marginal probability of each H is presented by the five linguistic terms (i.e. Very High, High, Medium, Low, and Very Low). To prioritise the PTSs' hazards, a utility values approach (U_{Rh}) developed by Yang (2001) is used in this study. Consequently, the output belief degree of each Hs is synthesized in one single value as follows:

$$RH = \sum_{h=1}^{5} \mathrm{P}(\beta_h) U_{Rh} \tag{4}$$

where $\mathrm{P}(\beta_h)$ is the H's belief degree for each linguistic term. $U_R = (1,2,3,4,5)$ and $U_{Rh} = (0,0.25,0.5,0.75,1)$ based on a linear distribution. *RH* is the utility of the selected hazard. The higher the RH value is, the significant the level of risk of the hazard.

E. Sensitivity analysis (Step 6)

Sensitivity analysis is the validation method used in order to corroborate the results. Forrester, *et al.*, (2001) previously mentioned that sensitivity analysis is a procedure that is usually performed, by a series of tests to examine how sensitive is the change that occurs in the model by setting different parameter values (i.e. changing input belief degrees). The sensitivity analysis must at least meet the following axioms (Yang *et al.*, 2009b; Jones, *et al.*, 2010):

Axiom 1: A slight increase/decrease in the belief degree of any of the linguistic variables of each input node leads to an increase/decrease in the output belief degree.

Axiom 2: The total influence measures of the combination of the probability variations from x parameters (evidence) should be always greater than the one from the set of $x - (y \in x)$ parameters (sub-evidence).

IV. Case Study

A case study is carried out in this paper, to determine how the methodology can be employed to evaluate the Hs associated with a specific PTS being investigated. This assessment is performed on the system of one of the world major petroleum producers. Due to confidentiality reasons, the associated ports and transport operators are kept anonymous. Three questionnaires were first constructed to collect the failure input information from experts involved in the investigated PTS. The selected experts are actively working at inshore and offshore terminals and petroleum ports, tankers, and pipeline systems, with over 20 years' working experience.

In order to evaluate the PTS' Hs, the system' Hs are identified (step one). Therefore, an extensive literature review has been carried out to determine the PTSs (ports, ships and pipeline systems) operational Hs. Furthermore, the Hs identified from literature review are further validated by experts through conducting a brainstorming technique within face-to-face meetings which took place in 2015 and 2016, respectively. Through conducting a literature review and gathering experts' personal experience, 42, 61, and 10 hazards have been identified within port, ship, and pipeline sub-systems, respectively as illustrated in Table I.

In step two, the established FRB table in section III.C is used. With the aim of gathering the failure information for the identified PTS' Hs, three questionnaires were constructed and presented to fifteen experts (five from each operational sector), each with more than 20 years' experience in the system's operation. The first questionnaire was designed to evaluate the 42 Hs related to the petroleum ports. This survey was sent to five experts in the port operation sector. The second and third questionnaires were designed to evaluate the Hs associated with the tankers and pipelines respectively. The participants were invited to evaluate each of the Hs in their operation sector with respect to the three risk parameters. The participants asked to indicate an appropriate assessment for the three attributes of each Hs by using the described linguistic grades in Tables II, III and IV.

After the authors received the feedbacks from the participants, the arithmetic mean was employed in order to collect the average of the three risk parameters of the 113 Hs (i.e. 42 (port) + 61 (ship) + 10 (pipeline)). The resulting values were then used in the form of prior probabilities (step 4). For example, for assessing the hazard of Company Policies (PPHC) by using the arithmetic averaging technique, the parameter *P Very High* is presented as a sample. Experts 1 - 5 have assessed the parameter $P_{Very\ High}$ as: 5%, 10%, 10%, 5%, and 10%. By using the arithmetic mean, the average degree of belief is 8%. The same technique is used to identify the belief degree for PPHC hazard parameters (Table VI) and the other 112 Hs.

Table VI: Prior probability of P_l, S_c and D_p for PPHC

Risk Parameters		**Average Degree of Belief in %**
P	**Very High**	8
	High	13.1111
	Medium	21. 1111
	Low	33. 8889
	Very Low	23.8889
S	**Very High**	10
	High	12. 7778
	Medium	22. 7778
	Low	29.4444
	Very Low	25
D	**Very High**	5.8889
	High	16.6667
	Medium	29.1111
	Low	27.2222
	Very Low	21.1111

In step three, BN based FMEA models have been developed. Based on the experts' analysis, P_l, S_c and D_p grades for each H were estimnated. By considering the complexity of the manual calculation, a computer software tool (i.e. Hugin software) is used to compute marginal probability for each of the 113 Hs that occur in the investigated PTS. The obtained degree of believe from step four for PPHC hazard is presented in Fig. 3.

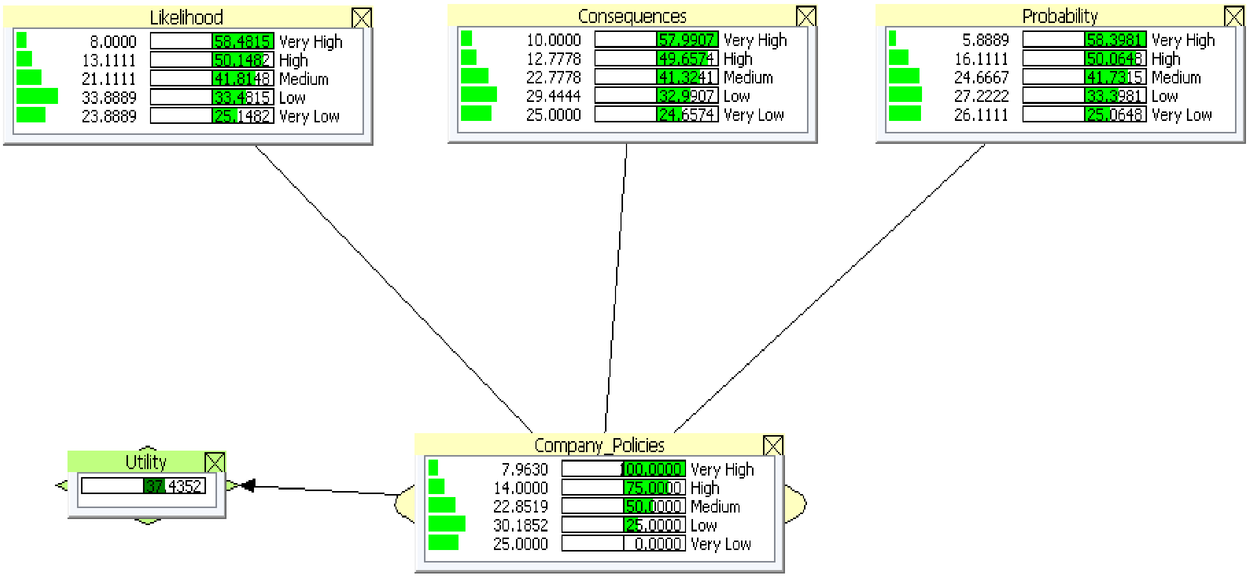

Fig.3: The analysis of PPHC by Hugin software

As a result, the analysis values of PPHC can be expressed by using Eq. 3 as follows:

$P(R_h \mid P_l, S_c, D_p) = (7.96, 14, 22.85, 30.18, 25)$

In step five, based on Eq. 4 and as shown in Table VII, the utility value of PPHC is evaluated as 37.43.

Table VII: The steps for calculating the utility value of PPHC

Rh	**Very High**	**High**	**Medium**	**Low**	**Very Low**
V_h	5	4	3	2	1
U_{Rh}	$\frac{5-1}{5-1} = 1$	$\frac{4-1}{5-1} = 0.75$	$\frac{3-1}{5-1} = 0.5$	$\frac{2-1}{5-1} = 0.25$	$\frac{1-1}{5-1} = 0$
$Ƥ\,(R_h)$	7.96%	14%	22.85%	30.18%	25%
$\sum_{h=1}^{5} Ƥ\,(R_h) = 7.96\% + 14\% + 22.85\% + 30.18\% + 25\% = 100\%$					
$Ƥ\,(R_h)\,U_{Rh}$	7. 96%	10.5%	11.42%	7.54%	0
$RH_{\mathrm{PPHC}} = \sum_{h=1}^{5} Ƥ\,(R_h) U_{rh} = 37.43$					

Table VIII: Utility value of the 42 Petroleum port hazards

	Hs	Utility value	Ranking
H 1	Company Policies	37.43	38
H 2	Company Standards	47.08	17
H 3	Management Procedure	47.27	16
H 4	Inattention	47.64	12
H 5	Neglect	47.45	13
H 6	Fatigue	43.29	28
H 7	Skills	47.41	14
H 8	Overfill	42.22	29
H 9	SOPs (Standard Operating Procedures) Not Followed	46.71	19
H 10	Overpressure	45.88	24
H 11	Release From Loading Arm/SBM	41.94	30

H 12	Understaffing	47.36	15
H 13	Breakdown of Communication	49.72	8
H 14	Communication Misunderstanding	50.42	6
H 15	Wrong Signals	47.78	11
H 16	Procedural Failure	54.44	1
H 17	Collision between Ship and Other Ship/Berth	53.75	3
H 18	Lack of Tools/Spare Parts	50	7
H 19	Inappropriate maintenance practice	46.71	19
H 20	Use of Inappropriate Tools/Spare Parts	46.62	21
H 21	Maintenance Omission	45.37	26
H 22	Lack of Communication System	50.60	5
H 23	Lack of Lighting System	46.25	23
H 24	Lack of Movable Facilities	40.92	33
H 25	A/C System Failure	41.62	31
H 26	Control System Failure	49.72	8
H 27	Instrument Failure	49.21	10
H 28	Valve Failure	44.08	27
H 29	Hose/Pump Failure	31.57	41
H 30	Gasket Failure	52.87	4
H 31	Pipeline Failure	46.43	22
H 32	Loading Arm/SBM Failure	46.94	18
H 33	Power Failure	54.21	2
H 34	Cathodic Protection Failure	45.55	25
H 35	Heavy Rainfall	41.57	32
H 36	Flood	35.92	39
H 37	Snow	24.95	42
H 38	Hurricane	33.70	40
H 39	Tornadoes	38.70	36
H 40	Lightning	38.24	37
H 41	Earthquake	39.94	34
H 42	Tsunami	38.97	35

Table IX: Utility value of the 61 Ship transportation hazards

	Hs	Utility value	Ranking
H 1	Main Engine Failure (Collision)	49.40	2
H 2	Bridge Navigation Equipment Failure (Collision)	44.28	15
H 3	Communication System Failure (Collision)	44.28	15
H 4	Wrong use of Navigation Equipment (Collision)	48.19	4
H 5	Lack of Communication (Collision)	40.14	35
H 6	Failure to Follow Operational Procedure (Collision)	40.21	33
H 7	Action To Avoid Collision (Collision)	49.19	3
H 8	Human Inattention (Collision)	42.29	26
H 9	Human Neglect (Collision)	44.93	11
H 10	Human Fatigue (Collision)	50.51	1
H 11	Human Skills (Collision)	44.93	12
H 12	Weather Condition (Collision)	44.58	13
H 13	Third Party Activity (Collision)	37.85	48
H 14	Main Engine Failure (Grounding)	43.61	19
H 15	Communication System Failure (Grounding)	43.05	22
H 16	Bridge Navigation Equipment Failure (Grounding)	41.67	28
H 17	Wrong use of Navigation Equipment (Grounding)	39.65	38
H 18	Lack of Communication (Grounding)	38.61	44
H 19	Failure to Follow Operational Procedure (Grounding)	39.24	41
H 20	Rout Selection (Grounding)	45.24	10
H 21	Using Inappropriate Chart (Grounding)	40.28	32
H 22	Human Inattention (Grounding)	39.58	39
H 23	Human Neglect (Grounding)	41.94	27

H 24	Human Fatigue (Grounding)	46.53	7
H 25	Human Skills (Grounding)	40.49	30
H 26	Weather Condition (Grounding)	43.99	18
H 27	Third Party Activity (Grounding)	40.42	31
H 28	Water Depth (Grounding)	43.05	22
H 29	Construction Failure (Hull Failure)	39.93	36
H 30	Corrosion (Hull Failure)	40.21	33
H 31	Maintenance Failure (Hull Failure)	46.46	8
H 32	Stowage Planning Failure (Hull Failure)	44.24	17
H 33	Collision (Hull Failure)	39.72	37
H 34	Grounding (Hull Failure)	44.31	14
H 35	Human Inattention (Fire/Explosion)	43.40	20
H 36	Human Neglect (Fire/Explosion)	45.49	9
H 37	Human Skills (Fire/Explosion)	42.68	25
H 38	Inert Gas/Ventilation System Failure(Fire/Explosion)	46.6	6
H 39	Electric Failure (Fire/Explosion)	43.19	21
H 40	Pumping Room Failure (Fire/Explosion)	38.19	46
H 41	Main Engine Failure (Fire/Explosion)	33.37	58
H 42	Heating system Failure (Fire/Explosion)	29.18	61
H 43	Spread of Fire From Other Object (Fire/Explosion)	38.58	45
H 44	Sabotage (Fire/Explosion)	37.71	50
H 45	Weather Condition (Fire/Explosion)	35.66	54
H 46	Pipe Failure (Equipment Failure)	37.36	51
H 47	Valve Failure (Equipment Failure)	34.51	55
H 48	Pump Failure (Equipment Failure)	37.85	48
H 49	Tank Gauging System (Equipment Failure)	32.99	59
H 50	Manifold Failure (Equipment Failure)	41.46	29
H 51	Power Failure (Equipment Failure)	37.22	52
H 52	Heating System Failure (Equipment Failure)	33.82	57
H 53	Loading Computer (Equipment Failure)	29.86	60
H 54	Maintenance Error (Equipment Failure)	39.31	40
H 55	Maintenance Omission (Equipment Failure)	38.96	42
H 56	Lack of Communication (Equipment Failure)	38.89	43
H 57	Procedural Failure (Equipment Failure)	34.1	56
H 58	Human Inattention (Equipment Failure)	38.05	47
H 59	Human Neglect (Equipment Failure)	42.71	24
H 60	Human Fatigue (Equipment Failure)	47.67	5
H 61	Human Skills (Equipment Failure)	36.29	53

Table X: Utility value of the 10 pipeline transportation hazards

	Hs	Utility value	Ranking
H 1	Sabotage	35.97	1
H 2	Workers Actions	32.22	9
H 3	Weather Condition	32.64	6
H 4	Geological Hazards	32.5	7
H 5	Material Failure	34.44	3
H 6	Construction Failure	32.78	4
H 7	Maintenance Failure	34.58	2
H 8	Failure to Follow Procedure	29.86	10
H 9	Internal Corrosion	32.78	4
H 10	External Corrosion	32.5	7

Based on the identified utility value for each of the identified PTS' Hs, the hazard Procedural Failure is the most important hazard within seaport system, followed by Power Failure, Wrong use of Navigation Equipment and Ventilation System Failure (see Table VIII). By using the same procedure, the hazards Ship Collision due to Human Fatigue, Ship Collision due to Main Engine Failure, Action to Avoid Collision, Sabotage, Pipeline System Maintenance Failure, and Pipeline Material Failure are the most important hazards within the tankers and pipelines respectively (see Table IX and Table X). After utilising the belief degree of and prioritising the 113 Hs associated with the PTSs (i.e. port and transportation modes' hazards), the hazard Procedural Failure (PTHP), is the most significant hazard in this system (see Table XI).

Table XI: Utility Value of the most significant hazards in each operational system within the PTSs

	Hs	Utility Value	Ranking
H16	Procedural Failure	54.44	1
H 33	Power Failure	54.21	2
H 17	Collision between Ship and Other Ship/Berth	53.75	3
H 10	Human Fatigue (Collision)	50.51	4
H 1	Main Engine Failure (Collision)	49.4	5
H 7	Action To Avoid Collision (Collision)	49.19	6
H 1	Sabotage	35.97	7
H 7	Maintenance Failure	34.58	8
H 5	Material Failure	34.44	9

In the final step (i.e. step five), two axioms are introduced in order to examine the sensitivity of the changes that are going to occur to the hazard marginal probability, by changing the prior probabilities of the three parent nodes. By performing axiom 1 (i.e. increasing the belief degree of Likelihood $_{Very\ High}$ =100%"), the belief degree value of the node "likelihood" is updated to be 100% "Very High" (see Fig. 4). As a result, the output value of the node PPHC $_{Very\ High}$ has become greater than its original value by changing its belief degree value from 8 % to 38.63 %.

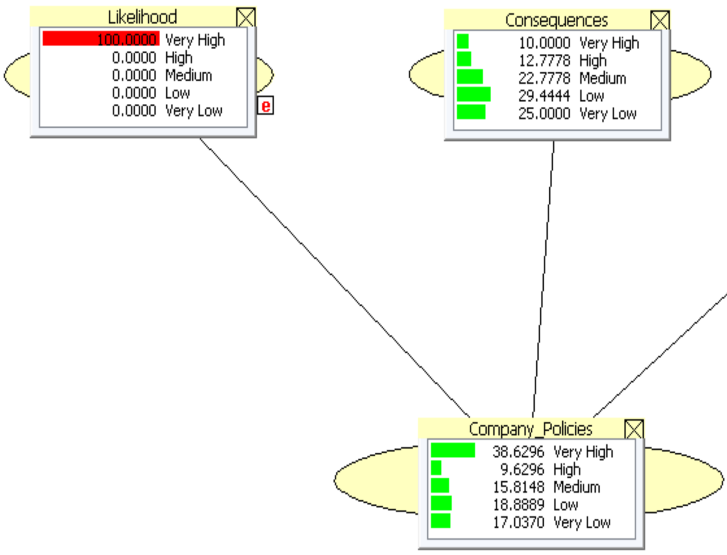

Fig. 4: Examine the sensitivity of PPHC by Hugin software given the evidence for node "$\boldsymbol{Likelihood_{Very\ High}} = \mathbf{100}$%"

Through preforming axiom 2 for the same hazard (i.e. increasing the belief degree for two nodes "Likelihood $_{Very\ High}$ and "Probability $_{Very\ High}$ =100%"), led to a change "PPHC $_{Very\ High}$ assessment output from 8% to 70%, as illustrate in Fig. 5.

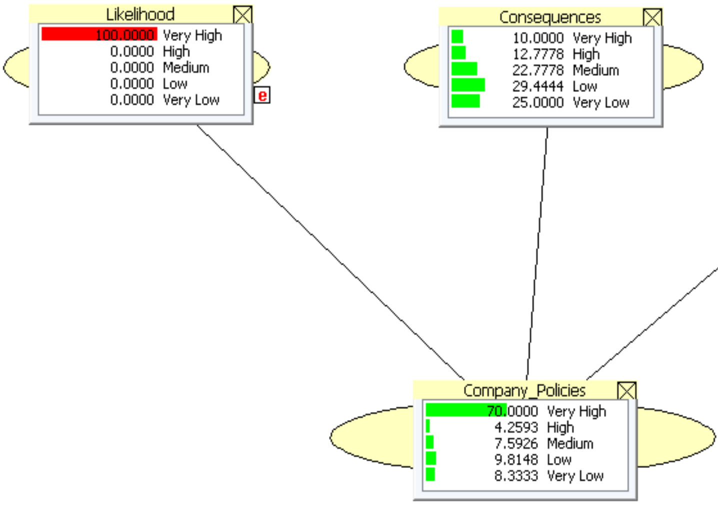

Fig. 5: Examine the sensitivity of PPHC by Hugin software given the evidence for node "$\boldsymbol{Likelihood_{Very\ High}} = \mathbf{100\%}$" and "$\boldsymbol{Probability_{Very\ High}} = \mathbf{100\%}$"

By carrying out axiom 1 (i.e. increasing the belief degree of Likelihood $_{Very\ High}$ =100%") and axiom 2 (i.e. increasing the belief degree for both "Likelihood $_{Very\ High}$ and "Probability $_{Very\ High}$ =100%") for all the hazards, the results of these axioms clarify the model's sensitivity whilst changing the inputs degree of belief (see Fig. 6). This highlights that output value keeps consistent with axiom 1 to axiom 2.

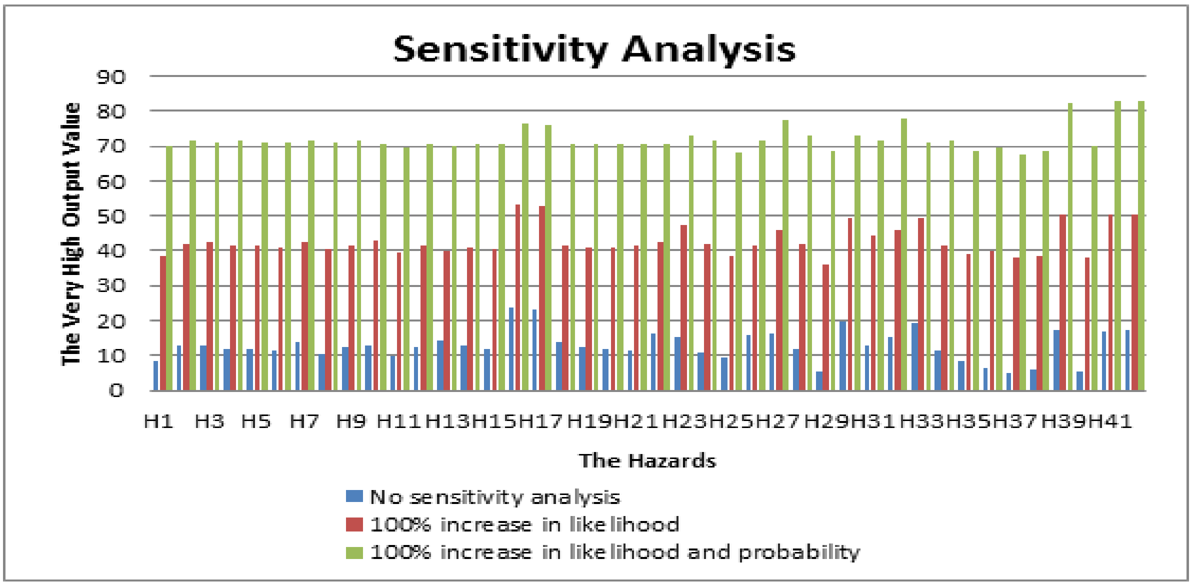

Fig. 6: The sensitivity analysis of the petroleum port system 42 hazards

V. Conclusion

Evaluation of PTS operational hazards is a key element for the system overall safety, and also can effectively assist decision-makers in enhancing its performance. This study is one of the first that deals with data uncertainty problems in PTSs from the perspective of a whole PTS system. In this paper, a mathematical model integrates FRB theory and BN to analyse the PTSs' operational hazards to overcome the disadvantages of these two methods. The FRBR method uses domain expert knowledge in the form of fuzzy IF-Then rules, and the BN mechanism to synthesize the rules for prioritising the PTSs' Hs.

In the proposed methodology, firstly, 113 hazards associated with the PTSs operations are identified. Secondly, an FRB with a belief structure in FMEA is established. Thirdly, the rules are aggregated by using the developed BN model. Fourthly, the PTSs' hazards are ranked by using the utility approach. Finally, the sensitivity for each of the identified hazards is examined by using a sensitivity analysis technique. The results from the case study reveal that the proposed method is capable of analysing the local levels of the PTSs and provide an improved evaluation technique for PTSs' risk assessment. In terms of the case study based on one of the world major petroleum producers, Procedural Failure, Ship Collision due to Human Fatigue and Sabotage are its PTS' most significant Hs. The results highlight the importance of human-related hazards in each of the three operational systems (i.e. ports, tankers and pipelines) within the PTSs. From previous engineering studies, human-related hazards have a significant impact on system operations, where the consequences of an operational mistake might lead to economic and environmental disasters. In addition, the results highlight that machine and natural-related hazards should not be neglected within the operation of PTSs, due to the severity of the consequences that might affect the environment and industry.

The proposed assessment methodology provides decision-makers with a rational risk-ranking technique for enhancing the safety of PTSs. In other words, the proposed method shows realistic and flexible results by describing the failure information based on real-life situations.

This paper mainly focuses on evaluating the local levels of the PTSs while it, for the first time, enables the risk of hazards in different sub-systems of PTSs to be tackled on the same universe. However, controlling the operational risk at a local level may not ensure the safety of the PTSs. In future work, the global level of the PTSs will be evaluated. In this regards, advanced uncertainty techniques such as evidential reasoning seems promising.

References

Aldridge, J.R., Taylor, J. and Dale, B.G., 1991. The application of failure mode and effects analysis at an automotive components manufacturer. *International Journal of Quality & Reliability Management*, *8*(3), pp.44-56.

Alyami, H., Lee, P.T.W., Yang, Z., Riahi, R., Bonsall, S. and Wang, J., 2014. An advanced risk analysis approach for container port safety evaluation. *Maritime Policy & Management*, *41*(7), pp.634-650.

Antão, P., Guedes Suares, C., Grande, O. and Trucco, P., 2009. Analysis of maritime accident data with BBN models. *Safety, reliability and risk analysis: theory, methods and applications. London, UK: Taylor & Francis Group*.

Ben-Gal, I., 2007. Bayesian networks. *Encyclopedia of statistics in quality and reliability*.

Bevilacqua, M., Braglia, M. and Gabbrielli, R., 2000. Monte Carlo simulation approach for a modified FMECA in a power plant. *Quality and Reliability Engineering International*, *16*(4), pp.313-324.

Cai, B., Liu, Y., Zhang, Y., Fan, Q., Liu, Z. and Tian, X., 2013. A dynamic Bayesian networks modeling of human factors on offshore blowouts. *Journal of Loss Prevention in the Process Industries*, *26*(4), pp.639-649.

Chin, K.S., Wang, Y.M., Poon, G.K.K. and Yang, J.B., 2009. Failure mode and effects analysis using a group-based evidential reasoning approach. *Computers & Operations Research*, *36*(6), pp.1768-1779.

Eleye-Datubo, A.G., Wall, A., Saajedi, A. and Wang, J., 2006. Enabling a powerful marine and offshore decision-support solution through Bayesian network technique. *Risk Analysis*, *26*(3), pp.695-721.

Emovon, I., Norman, R.A., Alan, J.M. and Pazouki, K., 2015. An integrated multicriteria decision making methodology using compromise solution methods for prioritising risk of marine machinery systems. *Ocean Engineering*, *105*, pp.92-103.

Feng, G., Zhang, J.D. and Liao, S.S., 2014. A novel method for combining Bayesian networks, theoretical analysis, and its applications. *Pattern Recognition*, *47*(5), pp.2057-2069.

Forrester, J.W., Breierova, L. and Choudhari, M., 2001. An introduction to sensitivity analysis. *Massachusetts Institute of Technology, Educational Materials*.

Golfarelli, M. and Rizzi, S., 2010. What-if simulation modeling in business intelligence. In *Business Information Systems: Concepts, Methodologies, Tools and Applications* (pp. 2229-2247). IGI Global.

Guimarães, A.C.F. and Lapa, C.M.F., 2007. Fuzzy inference to risk assessment on nuclear engineering systems. *Applied Soft Computing*, *7*(1), pp.17-28.

Herrán, A., de la Cruz, J.M. and De Andrés, B., 2010. A mathematical model for planning transportation of multiple petroleum products in a multi-pipeline system. *Computers & chemical engineering*, *34*(3), pp.401-413.

Hu S.P., Li X.D., Fang Q.G. and Yang Z. 2008. Use of Bayesian method for assessing vessel traffic risks at sea. *International Journal of Information Technology & Decision Making*, *7*(4), pp. 627-638.

Jiang, W., Xie, C., Zhuang, M. and Tang, Y., 2017. Failure mode and effects analysis based on a novel fuzzy evidential method. *Applied Soft Computing*, *57*, pp.672-683.

John, A., Paraskevadakis, D., Bury, A., Yang, Z., Riahi, R. and Wang, J., 2014. An integrated fuzzy risk assessment for seaport operations. *Safety Science*, *68*, pp.180-194.

Jones, B., Jenkinson, I., Yang, Z. and Wang, J., 2010. The use of Bayesian network modelling for maintenance planning in a manufacturing industry. *Reliability Engineering & System Safety*, *95*(3), pp.267-277.

Kavianian, H.R., Rao, J.K. and Brown, G.V., 1992. Application of hazard evaluation techniques to the design of potentially hazardous industrial chemical processes.

Kazemi, Y. and Szmerekovsky, J., 2015. Modeling downstream petroleum supply chain: The importance of multi-mode transportation to strategic planning. *Transportation Research Part E: Logistics and Transportation Review*, *83*, pp.111-125.

Keskin, G.A. and Özkan, C., 2009. An alternative evaluation of FMEA: fuzzy ART algorithm. *Quality and Reliability Engineering International*, *25*(6), pp.647-661.

Khakzad, N., Khan, F. and Amyotte, P., 2013. Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network. *Process Safety and Environmental Protection*, *91*(1), pp.46-53.

Khan, F.I. and Abbasi, S.A., 1998. Techniques and methodologies for risk analysis in chemical process industries. *Journal of loss Prevention in the Process Industries*, *11*(4), pp.261-277.

Li, K.X., Yin, J., Bang, H.S., Yang, Z. and Wang, J., 2014. Bayesian network with quantitative input for maritime risk analysis. *Transportmetrica A: Transport Science*, *10*(2), pp.89-118.

Liu, J., Yang, J.B., Wang, J. and Sii, H.S., 2005. Engineering System Safety Analysis and Synthesis Using the Fuzzy Rule-based Evidential Reasoning Approach. *Quality and Reliability Engineering International*, *21*(4), pp.387-411.

Liu, H.C., Li, P., You, J.X. and Chen, Y.Z., 2015. A Novel Approach for FMEA: Combination of Interval 2-Tuple Linguistic Variables and Gray Relational Analysis. *Quality and Reliability Engineering International*, *31*(5), pp.761-772.

Liu, H.C., Liu, L., Bian, Q.H., Lin, Q.L., Dong, N. and Xu, P.C., 2011. Failure mode and effects analysis using fuzzy evidential reasoning approach and grey theory. *Expert Systems with Applications*, *38*(4), pp.4403-4415.

Liu, H.C., Liu, L. and Liu, N., 2013. Risk evaluation approaches in failure mode and effects analysis: A literature review. *Expert systems with applications*, *40*(2), pp.828-838.

Martins, M.R. and Maturana, M.C., 2013. Application of Bayesian Belief networks to the human reliability analysis of an oil tanker operation focusing on collision accidents. *Reliability Engineering & System Safety*, *110*, pp.89-109.

Mokhtari, K., Ren, J., Roberts, C. and Wang, J., 2011. Application of a generic bow-tie based risk analysis framework on risk management of sea ports and offshore terminals. *Journal of hazardous materials*, *192*(2), pp.465-475.

Mokhtari, K., Ren, J., Roberts, C. and Wang, J., 2012. Decision support framework for risk management on sea ports and terminals using fuzzy set theory and evidential reasoning approach. *Expert Systems with Applications*, *39*(5), pp.5087-5103.

Nadkarni, S. and Shenoy, P.P., 2001. A Bayesian network approach to making inferences in causal maps. *European Journal of Operational Research*, *128*(3), pp.479-498.

Pak, J.Y., Yeo, G.T., Oh, S.W. and Yang, Z., 2015. Port safety evaluation from a captain’s perspective: The Korean experience. *Safety science*, *72*, pp.172-181.

Pillay, A. and Wang, J., 2003. Modified failure mode and effects analysis using approximate reasoning. *Reliability Engineering & System Safety*, *79*(1), pp.69-85.

Pootakham, T. and Kumar, A., 2010. A comparison of pipeline versus truck transport of bio-oil. *Bioresource technology*, *101*(1), pp.414-421.

Puente, J., Pino, R., Priore, P. and de la Fuente, D., 2002. A decision support system for applying failure mode and effects analysis. *International Journal of Quality & Reliability Management*, *19*(2), pp.137-150.

Rahman, N.S.F.A., Yang, Z., Bonsall, S. and Wang, J., 2015. A Fuzzy Rule-Based Bayesian Reasoning Method for Analysing the Necessity of Super Slow Steaming under Uncertainty: Containership. *International Journal of e-Navigation and Maritime Economy, 3*, pp.1-12.

Rao, P.G. and Raghavan, K.V., 1996. Hazard and risk potential of chemical handling at ports. *Journal of Loss Prevention in the Process Industries*, *9*(3), pp.199-204.

Ravi Sankar, N. and Prabhu, B.S., 2001. Modified approach for prioritization of failures in a system failure mode and effects analysis. *International Journal of Quality & Reliability Management*, *18*(3), pp.324-336.

Ren, J., Jenkinson, I., Wang, J., Xu, D.L. and Yang, J.B., 2008. A methodology to model causal relationships on offshore safety assessment focusing on human and organizational factors. *Journal of Safety Research*, *39*(1), pp.87-100.

Restrepo, C.E., Simonoff, J.S. and Zimmerman, R., 2009. Causes, cost consequences, and risk implications of accidents in US hazardous liquid pipeline infrastructure. *International Journal of Critical Infrastructure Protection*, *2*(1), pp.38-50.

Riahi, R., Robertson, I., Bonsall, S., Jenkinson, I. and Wang, J., 2013. A proposed methodology for assessing the reduction of a seafarer’s performance with insufficient recuperative rest. *Journal of Marine Engineering & Technology*, *12*(2), pp.11-28.

Ronza, A., Carol, S., Espejo, V., Vílchez, J.A. and Arnaldos, J., 2006. A quantitative risk analysis approach to port hydrocarbon logistics. *Journal of hazardous materials*, *128*(1), pp.10-24.

Russomanno, D.J., Bonnell, R.D. and Bowles, J.B., 1992, January. A blackboard model of an expert system for failure mode and effects analysis. In *Reliability and Maintainability Symposium, 1992. Proceedings., Annual* (pp. 483-490). IEEE.

Shahriar, A., Sadiq, R. and Tesfamariam, S., 2012. Risk analysis for oil & gas pipelines: A sustainability assessment approach using fuzzy based bow-tie analysis. *Journal of Loss Prevention in the Process Industries*, *25*(3), pp.505-523.

Sii, H.S., Ruxton, T. and Wang, J., 2001. A fuzzy-logic-based approach to qualitative safety modelling for marine systems. *Reliability Engineering & System Safety*, *73*(1), pp.19-34.

Song, W., Ming, X., Wu, Z. and Zhu, B., 2013. Failure modes and effects analysis using integrated weight-based fuzzy TOPSIS. *International Journal of Computer Integrated Manufacturing*, *26*(12), pp.1172-1186.

Spiegelhalter, D.J., Franklin, R.C. and Bull, K., 2013. Assessment, criticism and improvement of imprecise subjective probabilities for a medical expert system. *arXiv preprint arXiv:1304.1529*.

Tazi, N., Châtelet, E. and Bouzidi, Y., 2017. Using a hybrid cost-FMEA analysis for wind turbine reliability analysis. *Energies*, *10*(3), p.276.

Trucco, P., Cagno, E., Ruggeri, F. and Grande, O., 2008. A Bayesian Belief Network modelling of organisational factors in risk analysis: A case study in maritime transportation. *Reliability Engineering & System Safety*, *93*(6), pp.845-856.

Uğurlu, Ö., Köse, E., Yıldırım, U. and Yüksekyıldız, E., 2015. Marine accident analysis for collision and grounding in oil tanker using FTA method. *Maritime Policy & Management*, *42*(2), pp.163-185.

U.S. Energy Information Administration (EIA). (December 01, 2014). World oil transit chokepoints critical to global energy security. Available from: https://www.eia.gov/todayinenergy/detail.php?id=18991 [Accessed: 30th September 2017].

U.S. Energy Information Administration (EIA). (July 25, 2017). World oil transit chokepoints. Available from: https://www.eia.gov/beta/international/regions-topics.cfm?RegionTopicID=WOTC [Accessed: 30th September 2017].

Vinnem, J.E., Bye, R., Gran, B.A., Kongsvik, T., Nyheim, O.M., Okstad, E.H., Seljelid, J. and Vatn, J., 2012. Risk modelling of maintenance work on major process equipment on offshore petroleum installations. *Journal of Loss Prevention in the Process Industries*, *25*(2), pp.274-292.

Wang, G., Spencer, J. and Chen, Y., 2002. Assessment of a ship's performance in accidents. *Marine structures*, *15*(4), pp.313-333.

Wang, Y.M., Chin, K.S., Poon, G.K.K. and Yang, J.B., 2009. Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean. *Expert systems with applications*, *36*(2), pp.1195-1207.

Xu, K., Tang, L.C., Xie, M., Ho, S.L. and Zhu, M.L., 2002. Fuzzy assessment of FMEA for engine systems. *Reliability Engineering & System Safety*, *75*(1), pp.17-29.

Yang, J.B., 2001. Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties. *European journal of operational research*, *131*(1), pp.31-61.

Yang, Z., Bonsall, S. and Wang, J., 2008. Fuzzy rule-based Bayesian reasoning approach for prioritization of failures in FMEA. *IEEE Transactions on Reliability*, *57*(3), pp.517-528.

Yang Z., Bonsall S. and Wang J. 2009a. Use of hybrid multiple uncertain attribute decision making techniques in safety management. *Expert Systems with Applications*, *36*(2), pp. 1569-1586.

Yang Z., Bonsall S. and Wang J. 2009b. Use of fuzzy evidential reasoning in maritime security assessment. *Risk Analysis*, *29*(1), pp. 95-120.

Yang Z. and Wang J. 2015. Use of fuzzy risk assessment in FMEA of offshore engineering. *Ocean Engineering*, *95*, pp. 195-204.

Yuhua, D. and Datao, Y., 2005. Estimation of failure probability of oil and gas transmission pipelines by fuzzy fault tree analysis. *Journal of loss prevention in the process industries*, *18*(2), pp.83-88.

Zaman, M.B., Kobayashi, E., Wakabayashi, N., Khanfir, S., Pitana, T. and Maimun, A., 2014. Fuzzy FMEA model for risk evaluation of ship collisions in the Malacca Strait: based on AIS data. *Journal of Simulation*, *8*(1), pp.91-104.