A Fuzzy Rule-Based Bayesian Reasoning Approach for Risk Assessment of Petroleum Transportation Systems

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***Abstract*—Petroleum Transportation Systems (PTSs) play an important role in the movement of crude oil from its production sites to the end users. Such systems are complex because they often operate in a dynamic environment. Therefore, safe operations of the key components in the systems such as port and transportation are vital for the success of PTSs. 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 combining a Fuzzy Rule-Based (FRB) method and Bayesian Networks (BNs). This hybrid model has been found 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 Transportation Systems **(**PTSs) play a critical role in the flow of crude oil within a Petroleum Supply Chain (PSC). The PTSs enable the movement of crude oil from point A to point B, via land or sea. Ports and transportation modes are the basic elements in a PTS. To ensure the smooth flow of the product within the system, tankers and pipelines are the two most commonly used transportation modes [1, 2]. While ports act as a connecting point between the transportation modes, pipelines and tankers are used for inland and sea transportation respectively.

The U.S. Energy Information Administration [3] 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) is moved using PTSs. Petroleum production and consumption is highly associated with economic development. Therefore, it is crucial to identify and assess the hazards affecting PTSs and to ensure 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 the PTSs' operational hazards. In this paper, an established Fuzzy Rule-Based Bayesian Networks (FRBN) methodology is adapted. The Bayesian Network (BN) mechanism is used to aggregate all *IF-THEN* rules with belief structures, to produce the hazards' failure priority values. This assessment model is capable of aiding 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 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 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 PSC requires that a high priority is 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 in the movement of the 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 (i.e. port, ship, or pipeline), instead of a systematic perspective. For instance, studies such as [4-6] focused on the local level of the transportation modes, while studies such as [7, 8] focused on the petroleum ports. Within the context of supply chains, optimal risk controls at segment/local levels may not necessarily ensure the highest safety at the system/global level. It therefore reveals a research gap to be fulfilled.

The interlinked PTSs form a complex system. This is evidenced by the fact that there are multiple sub-systems (i.e. ports, tankers and pipelines) involved in its operations. Therefore, in this paper, each of these three key systems was first investigated, to identify the associated hazards associated. A failure in the PTSs is not necessarily due to the occurrence of a whole series of errors. A single failure or mistake might be the cause leading to the system's failure. The hazards within petroleum ports and transportation modes (i.e. ship and pipeline), have been analysed by carrying out a careful identification process (i.e. literature review). The identified hazards have been further verified by domain experts.

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 [9]. FMEA is one of the most common techniques in safety and reliability analysis. 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) [10].

However, the traditional FMEA method has some drawbacks that have been criticised by various researchers, such as the problem associated with the Risk Priority Number (RPN) [11-13].

To overcome these problems, and enhance the FMEA performance, uncertainty based techniques, such as artificial neural networks [18], Dempster-Shafer theory [15], fuzzy set theory [14], grey theory [12], evidential reasoning [16], and Monte Carlo simulation [17] have been proposed. FRBN was developed to overcome the FMEA drawbacks, in order to identify failure priority values, by using the mechanism of Bayesian Reasoning to conduct Fuzzy Rule-Based (FRB) risk inference [19].

A BN method was developed in the 1970s, based on the marriage of the basic Bayesian theory (developed by Bayes in the 1960s). A BN is a graphical model that provides a decision-support framework for problems involving uncertainty, complexity and probabilistic reasoning [20, 21]. In addition, a BN demonstrates the fundamental concept of probabilistic graphical models, or probabilistic networks.

A BN model is a Directed Acyclic Graph (DAG). 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 [22, 23]. The direction of the edge represents the relationship of each node to another node [19]. Parent, child, root and leaf nodes are the four types of nodes in the traditional BN. The edge starts from the parent node and ends with an arrowhead pointing to the child node. However, "root" nodes are those without links directed to parent nodes, and nodes without child nodes are called "leaf" nodes [22-24].

III. METHODOLOGY

For assessing the risk of the hazards associated with the PTSs, a model is constructed and an amalgamation of FRB in FMEA and BN is employed in this paper. A FRB is employed to model the conditional statements as well as 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' and transportation modes' operations within the PTSs, through the use of probabilistic reasoning. For analysing the PTSs' operational hazards, the analysis procedure is presented in Fig. 1 as follows:

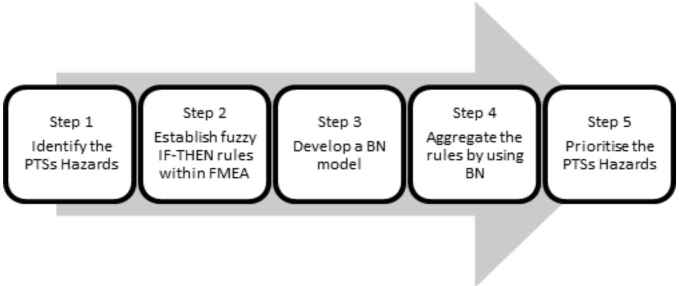

Fig. 1. The PTSs' assessment model flow chart

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. Therefore, in order to determine the Hs that affect the safety operations of a PTS, an extensive literature review and consultation with domain experts has been carried out. Consequently, the hazards that are most influential on the PTSs' operation are illustrated in Fig. 2.

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

As mentioned earlier in section II.B, 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 FMEA factors. P_l, S_c and D_p are the three risk parameters that are used in the IF part, while, 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 [8, 25, 26]. 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, where each parameter is defined based on knowledge accrued from past events.

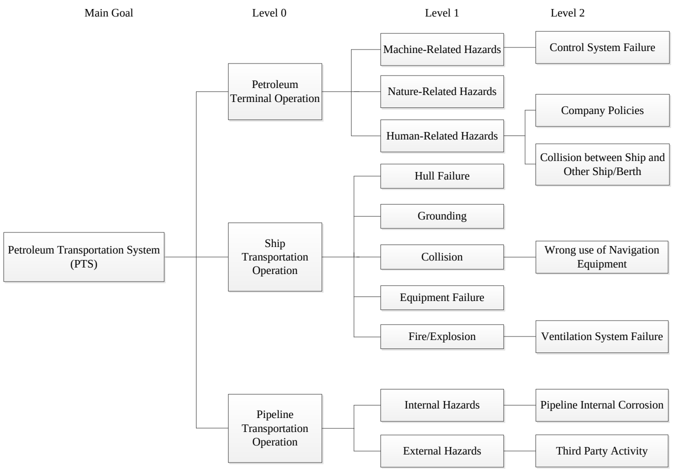

Fig. 2.Main hierarchical structure of the hazards in the PTSs

In the FRB, a belief structure is utilised to model the THEN part in the IF-THEN rule. For example:

- 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. To simplify this, the risk factors that obtain similar 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:

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

where $D(x)$ is the belief degree for Very High, High, Medium, Low, or Very Low in the THEN part, n represent 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 the Hs. For example, in Rule 1, three risk factors obtain 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. For risk evaluation of a petroleum port, pipeline and ship, 125 rules (5 × 5 × 5) with their belief degrees are presented [19] (see Table I).

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

In this step, various BN models have been developed. Each model represents one of the PTSs' hazard events that have been identified in the first step. BN is performed to confirm the relationship between the Hs and the established FRB with belief structure in FMEA, and to build a qualitative network capable of representing all the Hs and their dependencies (i.e. the three risk parameters).

Table I. 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	Very High	High	Medium	Low	Very Low
1	Very High (P1)	Very High (S1)	Very High (D1)	1	0	0	0	0
2	Very High (P1)	Very High (S1)	High (D2)	0.67	0.33	0	0	0
3	Very High (P1)	Very High (S1)	Medium(D3)	0.67	0	0.33	0	0
4	Very High (P1)	Very High (S1)	Low (D4)	0.67	0	0	0.33	0
5	Very High (P1)	Very High (S1)	Very Low (D5)	0.67	0	0	0	0.33
....	....	....	....	....	....	....	....	....
....	....	....	....	....	....	....	....	....
....	....	....	....	....	....	....	....	....
121	Very Low (P5)	Very Low (S1)	Very High (D1)	0.33	0	0	0	0.67
122	Very Low (P5)	Very Low (S1)	High (D2)	0	0.33	0	0	0.67
123	Very Low (P5)	Very Low (S1)	Medium (D3)	0	0	0.33	0	0.67
124	Very Low (P5)	Very Low (S1)	Low (D4)	0	0	0	0.33	0.67
125	Very Low (P5)	Very Low (S1)	Very Low (D5)	0	0	0	0	1

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 I 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

$$\mathrm{P}(R_i | L_1, C_1, P_2) = (0.67, 0.33, 0, 0, 0) \qquad (2)$$

Where " | " symbolises conditional probability.

The FRB constructed in FMEA can be modelled and transferred by using the BN technique in four nodes. Three parent nodes represent P_l, S_c and D_p of each H; these three parent nodes are connected to a 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 calculated, through simplifying the risk inference mechanism of the rule-base failure criticality evaluation. To marginalise Node R_h, the needed conditional probability table $P(R_h|P_l, S_c, D_p)$, can be obtain by using Eq. 2 and Table I, which symbolises a 5 × 5 × 5 × 5 table combination, having the values $P(R_h|P_l, S_c, D_p)$ $(h, l, c, p = 1,...,5)$.

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 through considering the perspective of multiple experts for supporting the prior probabilities calculation (i.e. $P(P_l)$, $P(S_c)$ and $P(D_p)$) 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 [10]:

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

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 [16] is used in this study. Consequently, the output belief degree of each Hs is aggregated in one single value as follows:

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

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

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 the confidentiality, 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). 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. Due to the word limitation, seven of the PTS' Hs are presented as sample of this evaluation process (see Fig. 2).

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 relating 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.

After the authors had 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 $P_{\text{Very High}}$ is presented as a sample. Experts 1 - 5 have assessed the parameter $P_{\text{Very High}}$ 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 II) and the other 112 PTSs Hs.

Table II. Prior Probability of L_k, C_s and P_b 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 steps three and four, BN based FMEA models have been developed. 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 (see Fig. 3).

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

P(R_h | P_l, S_c, D_p) = (7.96, 14.00, 22.85, 30.18, 25.00)

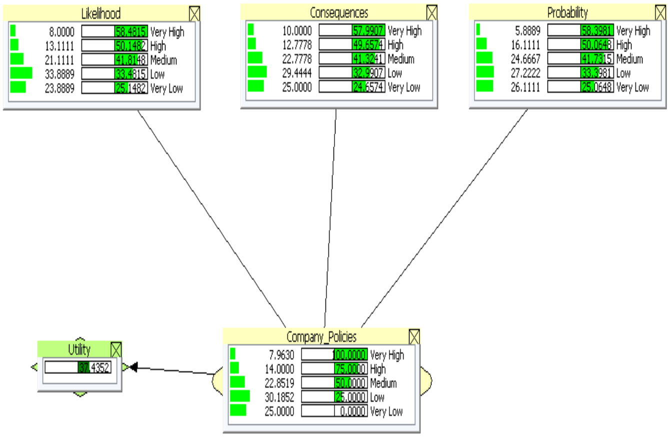

Fig. 3. The analysis of PPHC by Hugin software

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

Table III: 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}	$\frac{5-1}{5-1}=1$	$\frac{4-1}{5-1}=0.75$	$\frac{3-1}{5-1}=0.5$	$\frac{2-1}{5-1}=0.25$	$\frac{1-1}{5-1}=0$
$\mathrm{P}(R_h)$	8.2593%	13.7037%	22.8519%	30.1851%	25%
$\sum_{h=1}^{5}\mathrm{P}(R_h)=8.2593\%+13.7037\%+22.8519\%+30.1851\%+25\%=100\%$					
$\mathrm{P}(R_h)\,U_{Rh}$	8.2593%	10.2778%	11.4260%	7.5463%	0
$RH_{\mathrm{PPHC}}=\sum_{h=1}^{5}\mathrm{P}(R_h)U_{rh}=37.5093$					

Based on the identified utility value for each of the selected PTS' Hs, the hazard Collision between Ship and Other Ship/Berth (PTHS) is the most significant hazard, followed by Control System Failure (PTMC), Wrong use of Navigation Equipment (PSCW) and Ventilation System Failure (PSFV) (see Table IV). By using the same procedure, and after utilising the belief degree of 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.

Table IV: Utility Value of the Seven Hazards

	Hs	**Utility Value**
H1	Company Policies (PPHC)	37.43
H2	Control System Failure (PTMC)	49.72
H3	Collision between Ship and Other Ship/Berth (PTHS)	53.75
H4	Wrong use of Navigation Equipment (PSCW)	47.18
H5	Ventilation System Failure (PSFV)	46.59
H6	Pipeline Internal Corrosion (PPIP)	32.77
H7	Third Party Activity (PPET)	35.97

V. Conclusion

Evaluation of operational hazards of the PTSs is an important element for the safety of the overall system, and can aid decision-makers to enhance its performance. This study is one of the first studies that deals with the data uncertainty problems in PTSs as a one complete system. In this paper, a mathematical model integrates FRB theory and BN to analyse the PTSs' operational hazards in a complementary way. The FRBR method uses domain expert knowledge in the form of fuzzy IF-Then rules, and the BN mechanism to aggregate the rules for prioritising the PTSs Hs.

In the proposed methodology, firstly, operational hazards within the PTSs are identified. Secondly, an FRB with a belief structure in FMEA is established. Thirdly, the rules are aggregated by using the developed BN model. Finally, the PTSs' hazards are ranked by using the utility approach. 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, PTHP, Ship Collision due to Human Fatigue (PSCF) and PTHS are its PTS' most significant Hs. The results highlight the importance of human-related hazards within the PTSs. From previous engineering studies, human-related hazards have a significant impact on systems operation, where the consequences of an operational mistake might lead to economic and environmental disasters.

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 focused on evaluating the local levels of the PTSs. However, controlling the operational risk at local level may not ensure the safety of the PTSs. In future work, the global level of the PTSs will be evaluated. While the FRBN technique was used to assess the local level of the PTSs, the Evidential Reasoning (ER) approach can be applied to accomplish the PTSs evaluation, due to the approach's capability in synthesizing the risk from segments to a system level.

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