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Article

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Abstract

Petroleum refinery consists of numerous process units in operation, which are subjected to diverse accident risks in day-to-day operations under extreme operating conditions. Due to the complexity of petroleum refinery operations, any failure can lead to major accident and a huge financial loss for a petroleum refining company. However, petroleum refinery operations can be disrupted by various risk elements from the organization, technical, operational and external latent conditions. Risk elements are often inherent in operations, which can be based on uncertain knowledge, oversight and lack of perception of interactive events that can lead to disruption. In order to circumvent events that can cause disruption in a petroleum refinery, the criticality of the risk elements and their attributes that are associated with Petroleum Refinery Process Units (PRPU) operations need to be investigated. Therefore, there is a need to identify and assess the most critical risk elements and attributes that can interact to cause the disruption of operational reliability and availability of a petroleum refinery process unit. Hence, this article proposes a robust fuzzy linguistic assessment methodology for identification and assessment of PRPU risk elements and their attributes. The methodology deals with the main challenges of utilising expert's subjective judgements, in terms of the assessment of PRPU risk elements under uncertain situations. The result of the evaluation and ranking of PRPU risk elements and their attributes can provide salient risk information to duty holders and decision makers in the petroleum refinery in order to prioritise resources for risk management of the most critical attributes of the risk elements.

Keywords: Petroleum refinery process unit; Risk element; Risk management; Fuzzy Linguistic Preference Relation; Subjective Judgment.

1. Introduction

Petroleum refineries are complex infrastructures with various process units which can perform multiple phase operations. Petroleum Refineries Process Units (PRPU) are capital intensive and a constant flow production infrastructure with a high level of risk that can cause catastrophic accidents. However, the pressure of daily demand and commitment to production target in operations of most refineries around the globe has led to a strong push of safety boundaries, which has led to occurrences of major accidents. The breach of safety boundaries in a petroleum refinery domain is a result of combination of multiple interactive events. These series of interactive events often precipitate into the disruption of petroleum refinery operations. Based on historical cases of major accidents reported in the petroleum refining industry, it is evident that the build-up of interactive events is due to lapses in risk management. For instance, Saleh *et al.,* (2014), emphasize that the violation of safety diagnosis principles can affect operators risk perception towards emerging hazard, because of the shrinkage in knowledge and situation awareness of unfolding hazardous events.

Rodriguez *et al.,* (2011), explain that the meaningful implication of accident reporting can boost healthy safety climate, if the lesson learnt from the accident is utilized to enhance the prevention of future accidents. This has been one of the challenges in the risk management of petroleum refinery operations, because operators sometimes fail to utilise the primary mechanism from shared lessons learnt from major accidents. Rather, they predominantly focus their attention on safety performance indicators for the conception of the current safety level of operations in order to enhance organizational means of controlling risk. Major accidents in petroleum refineries such as ConocoPhillips-Humber refinery accident 2001, BP-Texas City refinery accident 2005, Tesoro Anacortes refinery accident 2010, Amuay oil refinery accident 2012, Chevron Richmond refinery accident 2012 and Bolshoy Uluy Krasnoyarsk refinery accident 2014, have raised important questions about the level of safety of petroleum refinery process units operations. According to Pasman *et al.*, (2013), maintaining adequate safety level from time to time is a difficult task because of the need to balance productivity and budget constraints. Knegtering and Pasman (2009), observe that lapses or failure of petroleum refining companies in their risk management process gradually builds up events, which eventually escalate into an accident. This sometimes occurs when corporate management fails to commit tangible resources and expertise to their risk management program (Wood *et al.*, 2013). Major accidents in petroleum refineries reveal that organization notions to safety, when accident risks are not perceived as a threat, has resulted in the degradation of safety attitude and neglect of early warning of risks. Owing to lack of insight of the operators or duty holder's in terms of hazard awareness, reveals, how, early warnings of undesired events could have been utilised to prevent a disastrous accident. This observation indicates that early warning is important in order to mitigate major accident risks, by providing situation awareness at the level in the organization where corrective actions can be implemented. According to Saleh *et al.*, (2014), the capability to detect or analyse a hazardous condition of a system or any safety degradation is tantamount to sustaining the safety of a system. An important part of the in-depth analysis conducted by Saleh *et al.*, (2014) indicates that lack of safety diagnosis ability in terms of perception or situation awareness can lead to potential concealment of petroleum refinery operations and hazard escalation.

Isimite and Rubini, (2016) and Manca and Brambilla (2012), emphasize that lack of resilience in organisational culture towards management of safety climate, process safety management, and human elements are contributory events that have led to an accident in process facilities including petroleum refineries. All the aforementioned issues, to a great extent, incubate safety barrier weakness, latent failures or allow the interactions of major accident hazards at different levels of operations. This shows that over time, the risk level of major accident hazards need to be systematically evaluated, in order to monitor safety level, and to provide the necessary risk information for complex decision making in a petroleum refinery domain. Several petroleum refinery process unit accidents have resulted in significant loss of lives, damage to properties, environmental pollution and disruption of economic activities due to fires, explosions, and process related failures.

According to the CSB (2007) investigation report on the 2005 BP-Texas City refinery accident, the catastrophe was initiated by looming organizational safety deficiencies at all stages of refinery process units operations. In addition, years of inconsistent reporting and recording of numerous near miss events and the lack of investigation on the growing risks to the mechanical integrity program for process equipment's of the Texas City refinery process units, massively contributed to the March 2005 disaster (Thomson, 2013; Knegtering and Pasman, 2009). Duty holders in the petroleum refinery industry tend to conceal salient information relating to major accident hazards or major events information, to protect their company reputation. Also, concealing major events information, portrays effective safety performance of their operations, to benefit from low insurance costs, and to create a lower risk perception about petroleum refinery operations to the regulators, government and the public (Nolan, 2014). Irrespective of the continuous development in safety design methods and operating procedures to overcome the high risks, which pose significant threat to life of personnel in PRPU environment, recordable losses due to major accidents still occur (Reniers and Amyotte, 2012; Vinnem *et al.,* 2012; Knegtering and Pasman, 2009). Therefore, it is crucial to readdress the issue of PRPU risk management relating to technical, organizational, operational and external risk problems, which can result in high risk of disruption of PRPU operations. In order to mitigate high risk of PRPU accident, it is important to analyse and prioritise the significant root causes of disruption of PRPU operations, in order to improve the risk management process in a PRPU domain. Therefore, critical risk elements and their associated attributes that can cause the disruption of a PRPU operation must be analysed and prioritised in order to determine their level of influence in contributing to the disruption of petroleum refinery operations. Proactively identifying and prioritising the risk elements of refinery process units is vital to risk management of petroleum refinery process units operations. The outcome of the evaluation and the prioritization process can be utilised to support decision makers and duty holders' aspirations in the petroleum refining industry, to enhance adequate decision-making, in terms of allocating resources efficiently. This paper is organised as follows. Section 2 presents a review of petroleum refinery risk elements. Section 3 presents a transparent description of the fuzzy linguistic assessment methodology, which was utilised in this study. Section 4 presents a case study analysis based on the methodology steps. Discussion and conclusion are presented in Sections 5 and 6.

2. Refineries process unit risk elements

The process of investigating and identifying critical risk elements for major hazard facilities like petroleum refinery process units has to be rigorous due to the complexity and diversity of their operations. The diagnosis of the risk elements and their attributes is often based on the accident investigation reports obtained from US Chemical Safety Board (CSB), UK Health and Safety Executive (HSE), and Analysis, Research and Information on Accidents (ARIA) database (ARIA (2012); CSB (2008); CSB (2001); HSE (2005);HSE (2003)and HSE (1997). The selection of the most critical risk elements and their attributes is carried out based on a comprehensive review of the major accidents from the aforementioned sources and brainstorming session with field experts in petroleum and gas refinery operations.

The risk elements and their associated attributes are represented in a hierarchical model. The model is an illustrative structure that depicts the common interactions of risk elements and their attributes, in order to analyse the disruption risk of PRPU operation. The overall effects of the risk elements and their attributes on PRPU operations can be quantify by incorporating an effective risk modelling methodology. The most significant risk elements that can cause interruption of petroleum refinery process units' safety and effectiveness in operation are enumerated in Table 1 and are further discussed in detail in Sections 2.1 to 2.4. The hierarchical model for petroleum refinery, process units' risk elements and their attributes is presented in Figure 1.

2.1 Technical risk elements

In a major hazard facility like a petroleum refinery, a variety of potentially hazardous products are being produced from crude oil, therefore, it is very important that the technical reliability of functional assets used in refinery process units is achieved at an optimum level to enable smooth operations. Any failure or deficiency in technical measures and performance can cause significant issues, such as process equipment, instrument, piping and utility system failures, which can interrupt smooth operations of refinery process units and cause huge financial consequences. Due to the complexity of technology to control and maintain operational reliability of refinery process units and other interconnected structures, there is a need to consider the aforementioned risk issues in order to identify and understand their interactions and influences with other potential hazards that can lead to accidents.

2.2 Operational risk elements

Refinery process units consist of several interconnections of complex equipment and machinery, which operate, in extreme conditions. Any deterioration in operating performance of the equipment and machinery under severe conditions in the refinery process unit environment, can result in a terrible operational hazard that can sometimes affect operations such as start-up, shutdown, maintenance, processing and storage (Shin 2014; Shin 2013; Khan and Amyotte, 2007). If a significant operational hazard is not critically addressed in an appropriate fashion, it may increase the probability of operational risks, which may result in higher operating costs, production loss, and dangerous situations that could cause a serious accident. In order to reduce high risk of operational failure and boost refinery process unit's operational availability and reliability, focus must be on operational risk elements that are considered as important initiator of disruptions to refinery process unit operations. Attributes such as deviations from operational procedure, operator incompetency, inadequate communications and inadequate maintenance procedure are identified as the most critical elements of disruption risk that can threaten refinery process units' operational reliability and availability.

2.3 Organizational risk elements

In the petroleum refining industry, organizational drive for efficiency and cost cutting can be a direct influence on overall safety perception and the safety level in the organization. Organization safety alertness and focus is crucial to proactive evaluation and management of safety in a high risk critical system like a petroleum refinery. High risk of process unit operations needs to be anticipated and appropriate organizational safety management approach should be adopted in a systematic manner to prevent the risk or to mitigate the consequences of risk. In a petroleum refinery, organizational safety management under-performance is a critical issue that has wreaked havoc by contributing to major refinery accidents. For example, the BP Texas refinery accident in 2005 and Chevron Richmond refinery accident in 2012 provides a clear view of the significant impact of organizational safety management under-performance, as a major factor in the build-up to the accident. In order to maintain a high level of organizational safety performance in petroleum and gas refineries, it is important to consider some significant root causes of organizational risk elements. Examples are inappropriate management procedure, inappropriate decision making, inadequate staffing, poor safety monitoring and auditing, and lack of safety training and drills.

2.4 External risk elements

To reduce the risk of petroleum refinery process unit accidents or mitigate the consequences, there is a need to address core external risk elements, which have contributed significantly to accidents in the past, in petroleum and gas refineries. Root causes of external risk element, such as natural hazards, sabotage and terrorist attacks, have contributed to disruption of PRPU operations.

Table 1: Significant risk elements and attributes

Level 2 risk element		Level 3 attributes	
E_1	Technical risk element	E_{11}	Process equipment failure
		E_{12}	Instrument failure
		E_{13}	Piping system failure
		E_{14}	Utility system failure
E_2	Organizational risk element	E_{21}	Inappropriate management policy/procedure
		E_{22}	Inappropriate decision making
		E_{23}	Inadequate staffing
		E_{24}	Poor safety monitoring/auditing
		E_{25}	Lack of safety training/drill
E_3	Operational risk element	E_{31}	Deviation from operation procedure
		E_{32}	Operator incompetency
		E_{33}	Inadequate communication
		E_{34}	Inadequate maintenance procedure
E_4	External risk element	E_{41}	Natural hazard
		E_{42}	Sabotage
		E_{43}	Terrorist attack

The hierarchical levels of the disruption risks elements presented above is based on robust literature review and meticulous study of major accidents in the oil and gas-refining domain. The main attributes of the risk elements (organizational, operational and external) describe human factor issues that have been recurrent incidents or part of contributory causes to major accidents. Notable accident reports and literatures such as CSB, (2007);

CSB (2014a) CSB (2014b); CSB (2014c); CSB (2017a); CSB (2017b); Qi et al. (2012) Baybutt, (2003) have all emphases the gap for improving knowledge on human/organizational factors as a vital paradigm to improve system safety in the oil and gas-refining refining sector. The element of human factors, which are represented as attributes associated with organizational, operational, and external in the hierarchy model present in this study are in concur with the underlying human and organizational factors broken down into categories in Gordon, (1998) and Bea, (1998). The hierarchical model integrate Schönbeck et al. (2010) ideology, which indicates that the operation of a highly risky socio technical system is reliant on the interaction of technical, organisational, managerial, human, social and environmental elements. Therefore, the hierarchical levels presents a corroborated picture of a causative model that fulfil the mechanism of a holistic approach for modelling disruption risks in a petroleum refinery domain.

Øien et al. (2011) conducted a research on the concepts safety indicator and risk indicator required to measure safety or risk. The main function of the concepts is a measure of safety performance to describe the safety level within an organization, establishment, or work unit. Their study is structured according to a combination of two perspective in relation to develop a search for accidents causals considering the path from technical, to human and organisational causes. Thus, there perspective is viewed in the light of a predictive versus a retrospective view. In retrospect, the measure of establishing the concepts of safety/risk indicator in terms of technical–human–organizational perspective and further extends to look at remote causes as external factor. Therefore, Øien et al. (2011) substantiate that the proactive approaches for the assessment of underlying factors' influence on safety/ risk can be illustrated by reversing the development moving from technical, to human, to organizational and to external factor for the purpose of accident investigation. This indicates that there is interdependences in terms of analysing the interaction path among the underlying factors. Nevertheless, there are challenges relating to dilemma with lack of data and lack of consensus in terms of prediction or estimating the path of dependencies. This have to do with biases of experts', because interdependencies of factors are measured based on different approaches, which can lead to oversimplification of influences path in a safety causal model (Mohaghegh et al., 2009). It is recognizable in risk modelling of major accidents in oil and gas refining domain that organizational factor, technical system failure coupled with human and external events are always defined in the scope of investigation.

Overview of the notion pathway of risk models from technical, to human, to organizational and external factor; differentiate the theoretical interest of researchers in the safety community. Hence, this study concentrate majorly on the background knowledge of experts, overview of lesson from major accident causal in relation to technical, organizational operational, and external element of disruption risks to determine the significance of risk elements and their attributes using a quantitative assessment method.

3. Methodology

In order to enhance a comprehensive risk management of petroleum refinery process unit operations, it is very important to carry out effective risk modelling of disruption risks of PRPU operations. Therefore, identifying and assessing the most significant PRPU risk elements and attributes will contribute a first phase of proactive risk management of PRPUs operations. A systematic approach based on utilising a Fuzzy Linguistic Preference Relation (FLPR) technique is incorporated into the methodology steps in this paper. The methodology will provide the flexibility to quantify experts' judgements qualitatively, in order to analyse the risks of PRPU in a situation where the availability and consistency of risk data is uncertain. The following steps present a transparent description of the methodology:

Step 1: Identification of risk elements and attributes.

Step 2: Develop a generic hierarchical model based on the risk elements and attributes.

Step 3: Linguistic assessment of risk elements and attributes.

Step 4: Apply an FLPR approach to determine the weight of all risk elements and attributes in the hierarchical structure.

Step 5: Ranking decision on each risk element and attributes according to the decreasing order of values.

3.1 Identification of risk elements and attributes of PRPU disruption

In view of the complexity of refineries, process units, structures and operations, the risk elements and attributes of disruption risk to PRPU operation are identified based on information extracted from a literature review of historical accident reports, literatures on accident analysis and brainstorming session with domain experts. The process of identification of PRPU risk elements and attributes is important to have in-depth knowledge and a real understanding of the PRPU disruption risks problem.

3.2 Hierarchical structure of petroleum refineries process unit disruption risk

An integrated hierarchical structure of refinery process units risk elements relationship, which incorporates important diverse details, is developed. The hierarchical structure for the PRPU risk elements provides systematic interpretation of risk elements interactions, such that an attribute at a lower level is linked to the risk element at higher level. For instance, attribute at lower levels as process equipment failure is a subset element of technological risk element at a higher level. For the purpose of this study, the term ‘element’ is used to describe part of something, particularly situations or activities that can initiate hazardous events (Wu *et al.*, 2015). Figure 1 presents the detailed hierarchical model for refinery, process units’ disruption risks.

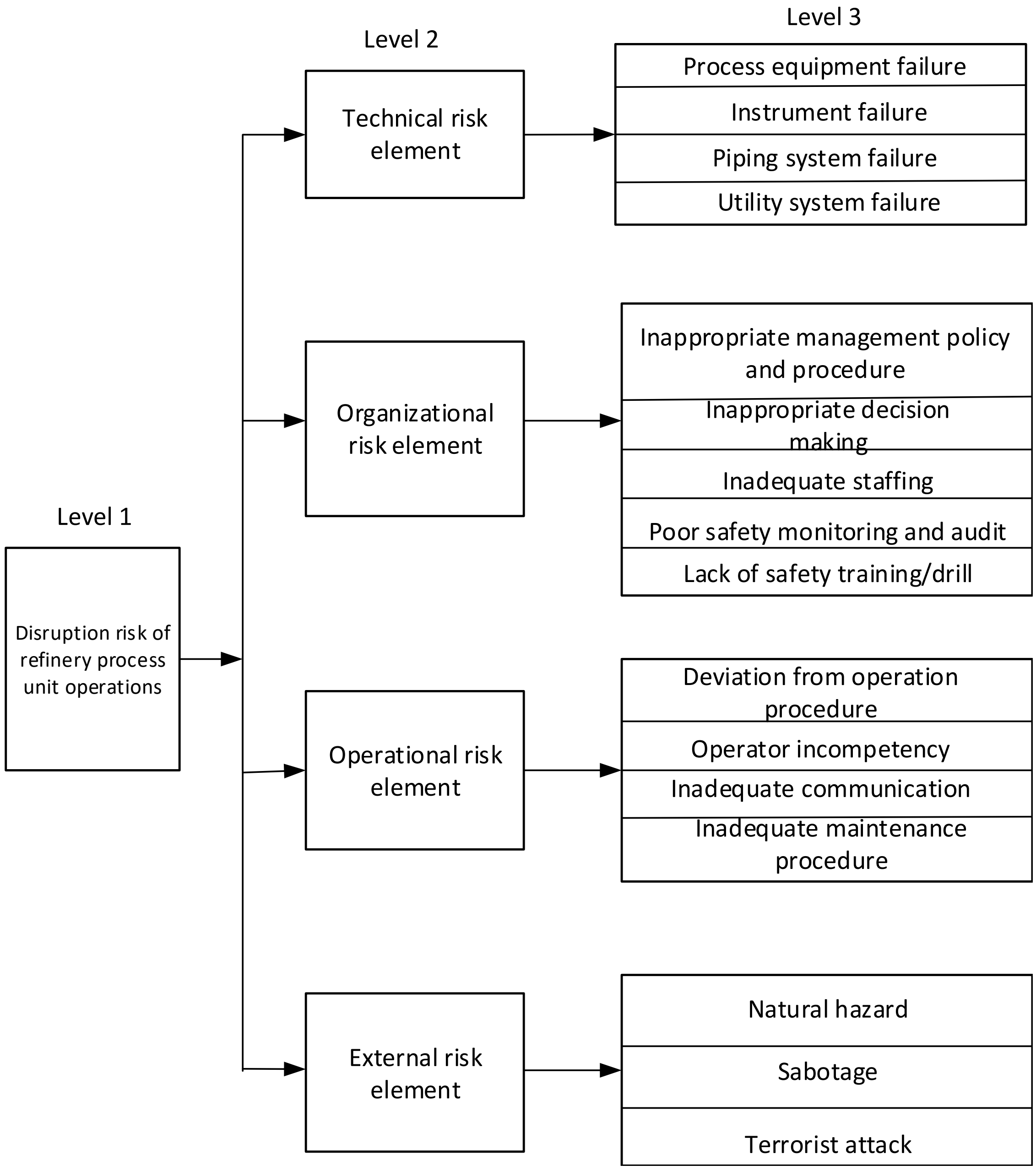

Figure 1. Hierarchical model for disruption risk of petroleum refinery process unit operation

3.3 Linguistic assessment of risk elements and attributes

Linguistic variables are regarded as expressions in natural or artificial language, which can be implemented to indicate the preference value of one criteria over another in a decision-based hierarchical model. For the purpose of this study, the idea of using the linguistic assessment variables is to deal with complexity or inconsistency of decision maker's opinion in order to express it in a quantitative manner. Linguistic expressions such as; absolutely not important, very strongly not important, essentially not important, weakly not important, equally important, very strongly important and absolutely important are used for pairwise comparisons of risk elements and attributes of disruption risk of PRPU operations. The linguistic expressions can expressed in fuzzy numbers based on the Triangular Fuzzy Number (TFN) proposed by (Chen and Hwang, 1992). TFN is a fuzzy set function that can be adopted to deal with the uncertainty and vagueness associated with decision makers' opinion in terms of solving practical problems. TFN provides decision makers' with a reasonable way to represent subjective and imprecise information in a logical manner. For a fuzzy number, $\tilde{P}$, TFN can be denoted by $\tilde{P} = (l, m, u)$ where l, m and u are expressed as lower, upper and median bounds of the fuzzy number. Based on operational laws of TFN in Wang and Chen (2008), the algebraic operations of any two triangular fuzzy numbers $\tilde{P}_1$ and $\tilde{P}_2$ can be expressed in the following manner:

Addition operation $\oplus$:

$$\tilde{P}_1 \oplus \tilde{P}_2 = (l_1,\, m_1,\, u_1) \oplus (l_2,\, m_2,\, u_2) = (l_1 + l_2\,,\; m_1 + m_2,\; u_1 + u_2\;) \tag{1}$$

Subtraction operation ⊖:

$$\tilde{P}_1 \ominus \tilde{P}_2 = (l_1, m_1, u_1) \ominus (l_2, m_2, u_2) = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \quad (2)$$

Multiplication operation ⊗:

$$\tilde{P}_1 \otimes \tilde{P}_2 = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) = (l_1 l_2, m_1 m_2, u_1 u_2) \cong \text{for } l_1 > 0, m_1 > 0, u_1 > 0. \quad (3)$$

Division operation ⊘:

$$\tilde{P}_1 \oslash \tilde{P}_2 = (l_1, m_1, u_1) \oslash (l_2, m_2, u_2) \cong \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right) \text{for } l_1 > 0, m_1 > 0, u_1 > 0 \quad (4)$$

Logarithm operation:

$$\log_k(\tilde{P}) = (\log_k l,\ \log_k m,\ \log_k u,) \text{ where k is base.} \quad (5)$$

Reciprocal operation:

$$(\tilde{P})^{-1} = (l, j, u)^{-1} \cong \text{ for } l, m, u > 0 \quad (6)$$

The TFN membership function is expressed in Equation (7).

$$\mu_{\tilde{p}} = f(x) = \begin{cases} \frac{x-l}{m-l} & l \leq x \leq m \\ \frac{u-x}{u-m} & m \leq x \leq u \\ 0, & \end{cases} \quad (7)$$

3.3.1 Triangular fuzzy conversion scale for pairwise comparison

Appropriate selection of fuzzy scale for pairwise comparisons of fuzzy opinions of experts is adopted from Wang and Chen (2011). The pairwise comparison scale is used in this study to establish the intensity of risk elements of petroleum refineries process units disruption risk based on expert judgement, which are represented using linguistic terms with corresponding triangular fuzzy numbers as shown in Table 2. In addition, Figure 2 shows the triangular fuzzy importance scale.

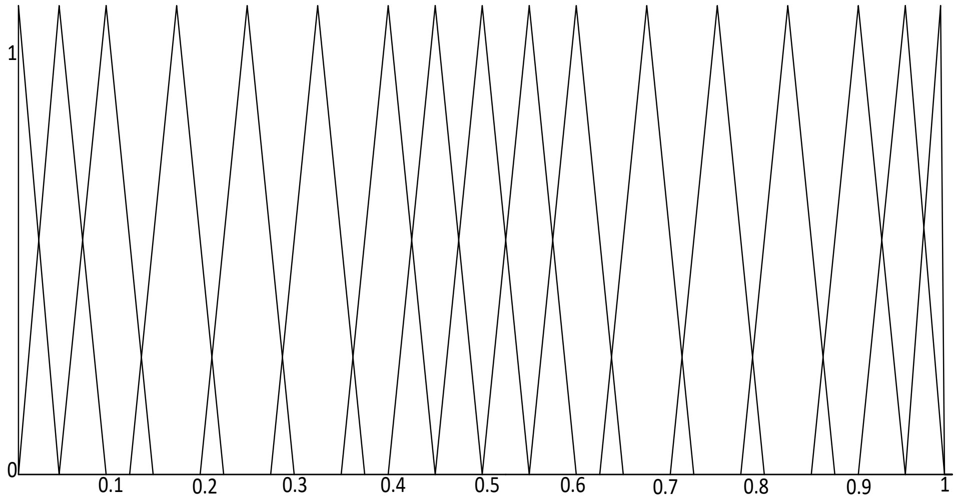

Figure 2. Triangular fuzzy importance scale adapted from Wang and Chen, 2011

Table 2: Fuzzy linguistic assessment variables

Linguistic variables	Triangular fuzzy number	Triangular fuzzy reciprocal scale
Equally important (EQ)	(0.45, 0.5, 0.55)	
Intermediate value between equally important and weakly more important (WE)	(0.5, 0.55, 0.6)	(0.4, 0.45, 0.5)
Weakly more important (WK)	(0.55, 0.6, 0.65)	(0.35, 0.4, 0.45)
Intermediate value between weakly more important and strongly more important (WS)	(0.625, 0.675, 0.725)	(0.275, 0.325, 0.375)
Strongly more important (ST)	(0.7,0.75, 0.8)	(0.2, 0.25, 0.3)
Intermediate value between ST and very strongly more important (VT)	(0.775, 0.825, 0.875)	(0.125, 0.175, 0.225)
Very strongly more important (VS)	(0.85,0.9,0.95)	(0.05, 0.1, 0.15)
Intermediate value between very strongly more important and absolutely important (VA)	(0.9, 0.95, 1)	(0, 0.05, 0.1)
Absolutely important (AB)	(0.95, 1, 1)	(0, 0, 0.05)
The inverse of the linguistic variables are (LWE), (LWK), (LWS), (LST), (LVT), (LVS), (LVA), (LVS), and (LAB). These inverse linguistic variables are represented as the triangular fuzzy reciprocal values.		

where LWE is the inverse of WE, LWK is the inverse of WK, LWS is the inverse of WS, LST is the inverse of ST, LVT is the inverse of VT, LVA is the inverse of VA, LVS is the inverse of VS and LAB is the inverse of AB.

3.3.2 Determining the weight of experts

It is important in a decision making process to determine the weights of experts employed, to give their subjective opinion on risk elements or attributes that can affect the reliability of a system under investigation. Therefore, the reliability and quality of experts' subjective opinions are based on the assigned weights of each expert using criteria such as experience/knowledge (EK), academic qualifications (AQ), and industrial position (IP). The aforementioned criteria have been presented in Table 3. Hence, the experts' weights can be calculated in a simple manner by using the Delphi method to obtain the weight score of each expert $(i = 1, \ldots., n)$. Then, the weighting scores of the experts and their weights can be obtained based on Equations 8 and 9.

$$\text{Weighting score of } E_i = \text{IP score of } E_i \; + \; \text{EK score of } E_i + \; \text{AQ score of } E_i \tag{8}$$

$$\mathrm{W}(E_i) = \frac{\text{Weight score of } E_i}{\sum_{i=1}^{n} \text{Weight score of } E_i} \tag{9}$$

where $\mathrm{W}(E_i)$ denotes the weight of expert i.

In this study, the integration of the fuzzy judgments of a group of experts concerning $n - 1$ pairwise comparison values $\left(\tilde{p}_{12}\,, \tilde{p}_{23}\,, \ldots.. \; \tilde{p}_{(n-1)n}\right)$ was utilised to construct a consistent fuzzy linguistic preference relation matrix. The aggregated fuzzy judgment values of 'n' experts can be estimated using Equation 10.

$$\bar{\tilde{p}}_{ij} = \; \left\{\left(W(E_1)\otimes\tilde{p}_{ij}^{1}\right) \oplus \left(W(E_2)\otimes\tilde{p}_{ij}^{2}\right) \oplus \ldots \ldots \ldots \oplus \left(W(E_n)\otimes\tilde{p}_{ij}^{\mathrm{n}}\right)\right\} \tag{10}$$

where $\bar{\tilde{p}}_{ij}$ is the integrated fuzzy judgment values of 'n' decision makers and $\tilde{p}_{ij}^{\mathrm{n}}$ indicate the fuzzy judgment value of expert *n*.

Table 3: Weighting scores for experts

Criteria	Categories	Score
Industrial position (IP)	Petroleum refinery manager/ Refinery Consultant	5
	Senior (refinery engineer/process engineer/ process safety manager)	4
	Process safety analyst	3
	Junior engineer	2
	Technician	1
Experience / knowledge (EK)	≥ 20 years	5
	11- 20 years	4
	6-10 years	3
	1-5 years	2
	None of the above	1
Academic qualifications (AQ)	PhD	5
	Master degree	4
	Bachelor degree	3
	HND	2
	HNC	1

3.4 Application of an FLPR process for weight estimate

In this study, the assessment of the relative weight of the risk elements and their attributes that can cause the disruption of a petroleum refinery process unit operations is important, in order to prioritize the risk elements and their attributes according to their levels of significance. The process will enhance the understanding of their impact in terms of disruption of PRPU operations. The FLPR procedure, which was presented in Section 3, is utilised in the assessment of PRPU risk elements and their associated attributes, in order to determine the degree of their importance.

The FLPR procedure lessens the difficulty and the inconsistency associated with the evaluation of a complex and sensitive hierarchical model problem (Wang and Chen, 2011; Huang *et al.*, 2011). In terms of utilising the FLPR procedure in the estimation of the importance weights of the PRPU risk elements and their attributes, it provides the benefit of maintaining consistency of a pairwise comparison matrix of experts judgement or preferences (Wang and Chang 2007:Wang and Chen, 2008; Chen *et al.*, 2011; Wang and Chen, 2011). In order to avoid uneven deductions in the assessment and ranking process of PRPU risk elements and their attributes, the FLPR procedure provides the flexibility for consistent comparability of the decision makers' preference by using fuzzy linguistic assessments variables.

When using the FLPR approach, it is quite easy to avoid exasperation in collecting a consistently sound judgement without prejudice from experts when using a questionnaire (Lu *et al.*, 2013). Using FLPR approach is much more convenient and reasonable to avoid a complex pairwise comparison and to check for inconsistencies in the decision matrices. The schematic of the FLPR methodology is presented in Figure 4.

3.4.1 Fuzzy linguistic preference relations (FLPR)

Wang and Chen (2005, 2008, and 2010) developed the FLPR method. The method involves utilizing fuzzy linguistic assessment variables to construct fuzzy linguistic preference relation matrices based on consistent fuzzy preference relation. Chen *et al.*, (2011), Wang and Chen (2011), Wang and Lin (2009) further used FLPR method in a suitable manner to solve multi-criteria decision-making problems. In a decision modelling problem, the preference of a decision maker when comparing a set of criteria $X = (x_1, \dots \dots, x_n)$ is depicted by $n \times n$ preference relation matrix $\boldsymbol{P} = [p_{ij}]$. $p_{ij} = P(x_i, x_j)$, for all $i, j \in \{1, \dots \dots, n\}$. p_{ij} is depicted as the degree of importance of criterion x_i over criterion x_j. Supposing $p_{ij} = 0.5$, it indicates that there is no difference between x_i and x_j ($x_i \sim x_j$); $p_{ij} > 0.5$ indicates that x_i is preferred to x_j ($x_i > x_j$); and

$p_{ij} = 1$ indicates that x_i is absolutely preferred to x_j, and $p_{ij} = 0$ shows that x_j is absolutely preferred to x_i. Hence, the preference matrix, ***P*** is assume to be an additive reciprocal given that $p_{ij} + p_{ji} = 1$ for all $i, j \in \{1, \dots., n\}$. The rationale for developing a fuzzy linguistic preference relations matrix for a given set of criteria X is based on the consistent fuzzy preference relation concept and fuzzy linguistic assessment variables. Fuzzy linguistic assessment variables are generally depicted as $\tilde{P} = (p_{ij}) = (p_{ij}^l, p_{ij}^m, p_{ij}^u)$, where p_{ij}^l and p_{ij}^u indicates the lower and the upper bounds of the fuzzy number $\tilde{P}$, while p_{ij}^m relatively indicates the median value instead of crisp values $\widetilde{P} = (p_{ij})$. If the above preference relation matrix complies with additive reciprocal consistency, then the following propositions are equivalent.

Propositions

$$
\begin{aligned}
&p_{ij}^l + p_{ji}^u = 1 \ \forall i, j \in \{1, \dots \dots.., n\} \\
&p_{ij}^m + p_{ji}^m = 1 \ \forall i, j \in \{1, \dots \dots.., n\} \\
&p_{ij}^u + p_{ji}^l = 1 \ \forall i, j \in \{1, \dots \dots.., n\} \\
&p_{ij}^l + p_{jk}^l + p_{ki}^u = \tfrac{3}{2} \ \forall i < j < k, \\
&p_{ij}^m + p_{jk}^m + p_{ki}^m = \tfrac{3}{2} \ \forall i < j < k, \\
&p_{ij}^u + p_{jk}^u + p_{ki}^l = \tfrac{3}{2} \ \forall i < j < k, \\
&p_{i(i+1)}^l + p_{(i+1)(i+2)}^l + \dots\dots. + p_{(j-1)j}^l + p_{ji}^u = \tfrac{(j-i+1)}{2} \ \forall i < j, \\
&p_{i(i+1)}^m + p_{(i+1)(i+2)}^m + \dots\dots. + p_{(j-1)j}^m + p_{ji}^m = \tfrac{(j-i+1)}{2} \ \forall i < j, \\
&p_{i(i+1)}^u + p_{(i+1)(i+2)}^u + \dots\dots. + p_{(j-1)j}^u + p_{ji}^l = \tfrac{(j-i+1)}{2} \ \forall i < j,
\end{aligned}
\tag{11}
$$

In the case of decision matrix with entries which are in the interval of [-c, 1+c] given $(c > 0)$ rather than interval [0,1], the following transformation function is used to transform the obtained fuzzy numbers to preserve the reciprocity and additive consistency f: [-c, 1+c] → [0,1].

$f\ (x^l) = \frac{x^l + c}{1+2c}\ , f\ \ (x^m)\ = \frac{x^m + c}{1+2c}\ \ ,\ \ f(x^u) = \frac{x^u + c}{1+2c}$ (12)

where $f\ (x^l)$, $f(x^m)$ and $f(x^u)$ depict transform functions for the lower, medium and upper bound of entries in a decision matrix that are in the interval [-c, 1+c]. x^l , x^m, x^u are defined as the lower, medium and upper bound values of all elements of a fuzzy linguistic preference relation (FLPR) matrix. In addition, c is the least value of all elements in FLPR matrix, which are not in interval of [0,1].

3.4.2 Fuzzy linguistic preference relation procedure for weighing and ranking

Step 1. Decision makers express their fuzzy opinions on a set of alternatives X = $\{x_1 , x_2 \dots \dots x_n\}$ in a decision problem with pairwise comparisons of the alternatives using fuzzy linguistic assessment variable and develop an incomplete consistent FLPR matrix $\tilde{P} = (\tilde{p}_{ij})_{n\times n}$ with only n-1 judgments $\{p_{12},\ p_{23,} \dots \dots \dots, p_{n-1n}\}$.

Step 2. Develop a complete FLPR matrix $\bar{\tilde{P}} = (\bar{\tilde{p}}_{ij})_{n\times n}$ by adopting the known elements in $\tilde{P}$ and the reciprocal additive propositions to calculate the unknown elements in $\tilde{P}$.

Step 3 Applying linguistic averaging operator to determine the average $\widetilde{A_\iota}$ of the *i*th alternative over all other alternatives in order to obtain the fuzzy weights of all alternatives.

$\widetilde{A_\iota} = \frac{\sum_{j=1}^{n} \bar{\tilde{p}}_{ij}}{n}$ for all i (13)

to calculate the averaged $\widetilde{A_\iota}$ of the *i*th alternative over other alternatives.

The weight $\widetilde{W}$ of each alternative is estimated as:

$\widetilde{W} = \widetilde{A_\iota} / \sum_{i=1}^{n} \widetilde{A_\iota}$ (14)

Step 4. Defuzzification process of final fuzzy weight values of alternatives is based on the adoption of defuzzification techniques such as the Centre Of Area (COA), fuzzy mean and spread method and other methods like Mean Of Maximum (MOM), and α cut. A simple approach using fuzzy mean and spread method by (Lee and Li, 1988) is utilized to obtain the crisp value of triangular fuzzy values. The fuzzy mean and spread method is reliable in terms of defuzzifying and ranking of fuzzy numbers because of its easiness to determine the optimum alternatives. The fuzzy mean and spread method for defuzzification is expressed as:

$$\mathrm{x}(\widetilde{U}_i) = (l + m + u)/3 \tag{15}$$

$\mathrm{x}(\widetilde{U}_i)$ represent the fuzzy mean of a TFN, where l and u depict the lower and the upper bound of the TFN, and m is the median value.

Step 5. Determination of the optimum alternative from the highest value of fuzzy mean $\mathrm{x}(\widetilde{U})$ values of all alternatives.

Using the stated procedure above, a pairwise comparison FLPR matrix can be constructed easily based on $(n-1)$ judgments for n criteria or alternatives.

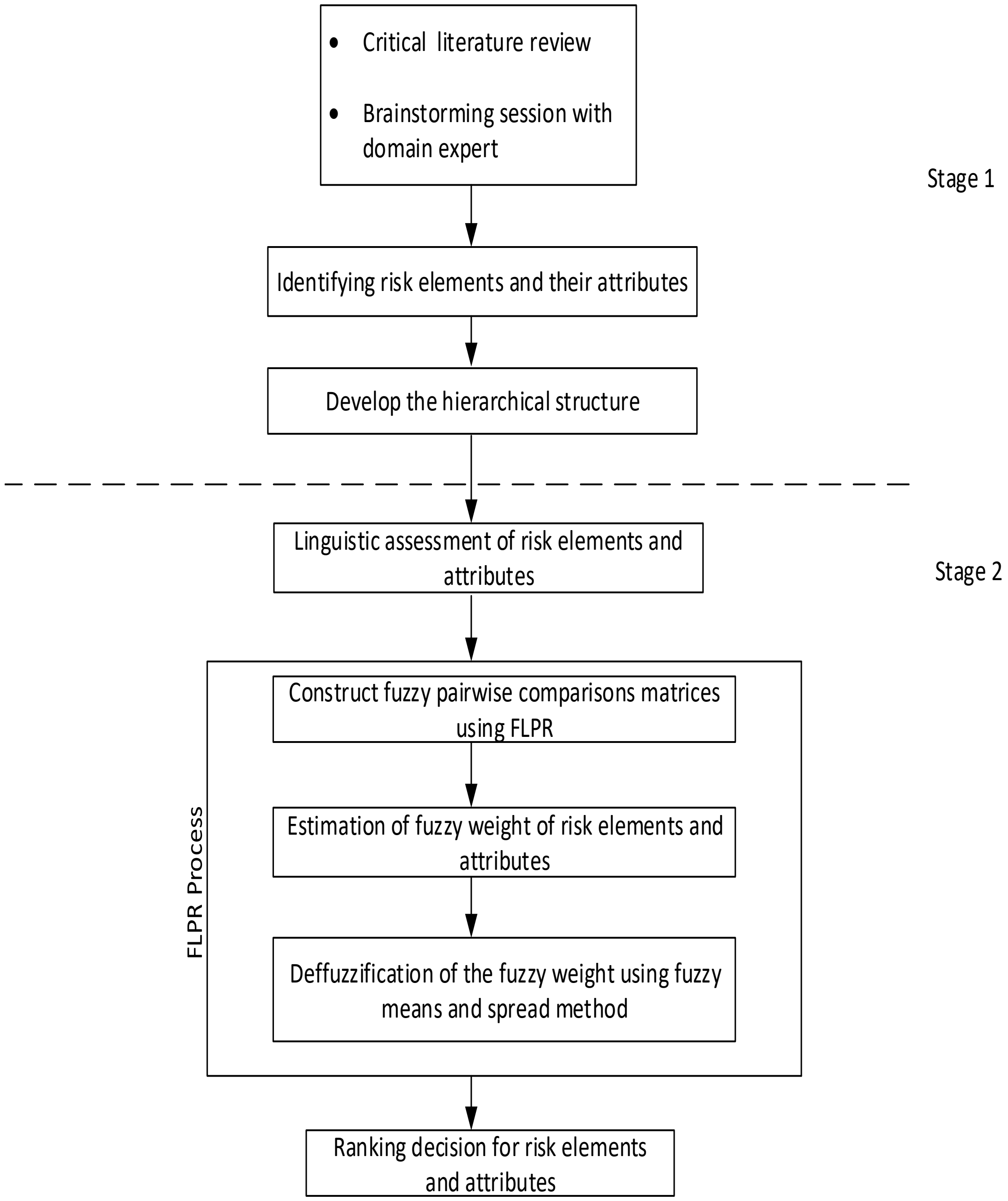

Figure 4. Schematic of FLPR methodology for assessment and ranking of disruption risks of PRPU operation

4. Case study

A case study of an onshore complex petroleum refinery, with over 20 years of operation, reasonable management of change in organizational structure and policies, and fairly reliable safety standards, is considered for investigation. With the aim of reducing high risk of disruption of PRPU operation, the major challenge is how to determine the importance level of the risk elements and their attributes, which has been identified and approved by experts as the significant causes of disruption of PRPU operations. For the purpose of this study, six experts are successfully convinced to participate in the assessment process.

- Step 1: Identify risk elements and attributes associated with the disruption of PRPU operation

Critical literature review and brainstorming sessions with experts and scholars having years of practical experiences can provide a comprehensive understanding of petroleum refinery process unit operations. This will provide the basic information for identification of significant risk elements and attributes that are observed and perceived to be a significant threat to PRPU operations. In this study, four major risk elements and sixteen attributes are considered as the major threat to PRPU operations.

- Step 2: Develop the hierarchical structure

The relationship between the four major risk elements and sixteen attributes that are identified is presented in the hierarchical structure. The hierarchical structure provides reliable information for the risk evaluation process in order to enhance effective risk management of PRPU operations.

- Step 3: Linguistic assessment of risk elements and attributes

The linguistic variable for pairwise comparison rating for the risk elements and their attributes are presented in Table 2. The pairwise comparisons of risk elements and their attributes in the hierarchical structure are established based on the experts' judgement. A questionnaire was provided to experts with 5 to 20 or more years' of experience, in order to obtain their opinion on the disruption risk of refinery process unit operations. The experts conduct the pairwise comparisons of the risk elements with respect to the goal. They also compared the attributes with respect to the risk elements. The weights of the experts that gave the judgements on the pairwise comparisons of the risk elements and their attributes are obtained. Table 4 shows the experts weights based on Delphi evaluation procedure.

Table 4: Weight of experts

Position	Experience/ knowledge proficiency	Qualification	Weighting factor	Weight of experts
Consultant	10 years	PhD	5+3+5 = 13	$\frac{13}{74}$ = 0.176
Senior engineer	5 years	Masters	4+2+4 = 10	$\frac{10}{74}$ = 0.135
Senior engineer	Over 20 years	Bachelor degree	4+5+3 = 12	$\frac{12}{74}$ = 0. 162
Senior manager	Over 20 years	PhD	5+5+5 = 15	$\frac{15}{74}$ = 0.202
Senior engineer	5 years	Masters	4+2+4 = 10	$\frac{10}{74}$ = 0.135
Senior manager	Over 15 years	PhD	5+4+5 = 14	$\frac{14}{74}$ = 0.19
			74	1

To determine the overall value of experts for the pairwise comparison of risk elements and their attributes, the weight of each expert and their rating were aggregated. The six expert judgments assigned to the pairwise comparison of risk elements are used to calculate the overall experts' judgement on each risk element and their attributes' in the hierarchical model. Table 5 shows the linguistic variables assigned by the experts for pairwise comparisons of the risk elements with respect to the goal. The judgment of the six experts for the pairwise comparison of risk elements, and the aggregated value of the six expert judgement for risk elements with respect to the goal are presented in Tables 6 and 7. Furthermore, each expert's linguistic judgment of all the attributes in regard to the risk elements is presented in Table 8.

Table 5: The linguistic terms of expert judgement for pairwise comparisons of risk elements

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	
E_1	LST	ST	EQ	VS	LST	WS	E_2
E_2	VS	WS	LST	LVT	VS	EQ	E_3
E_3	LVT	ST	LST	ST	VS	VS	E_4

Table 6: Judgement of six experts for risk elements

	Expert1(0.176)	Expert 2 (0.135)	Expert 3 (0.162)	Expert 4 (0.202)	Expert 5 (0.135)	Expert 6 (0.19)	
E_1	(0.2, 0.25, 0.3)	(0.7, 0.75, 0.8)	(0.45, 0.5, 0.55)	(0.85, 0.9, 0.95)	(0.2, 0.25, 0.3)	(0.625, 0.675, 0.725)	E_2
E_2	(0.85, 0.9, 0.95)	(0.625,0.675, 0.725)	(0.2,0.25,0.3)	(0.125, 0.175, 0.225)	(0.85, 0.9, 0.95)	(0.45, 0.5, 0.55)	E_3
E_3	(0.125, 0.175, 0.225)	(0.7, 0.75, 0.8)	(0.2, 0.25, 0.3)	(0.7, 0.75, 0.8)	(0.85, 0.9, 0.95)	(0.85, 0.9, 0.95)	E_4

Table 7: Aggregated value of experts on pairwise comparisons of risk elements

Risk elements	Aggregated expert value	Risk elements
E_1	(0.52,0.57,0.62)	E_2
E_2	(0.49,0.54,0.61)	E_3
E_3	(0.56,0.61,0.67)	E_4

Table 8: The linguistic terms of expert judgement for pairwise comparisons of attributes (FLRP)

		Expert1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	
E_1	E_{11}	LVS	LST	EQ	VS	LST	EQ	E_{12}
	E_{12}	ST	VS	AB	EQ	VS	VS	E_{13}
	E_{13}	VS	ST	LVS	VT	VS	WS	E_{14}
E_2	E_{21}	VS	EQ	LST	ST	VT	VT	E_{22}
	E_{22}	ST	ST	VS	WS	EQ	VS	E_{23}
	E_{23}	LST	LST	VS	VS	LVS	LST	E_{24}
	E_{24}	LVS	WS	VS	EQ	LVS	LAB	E_{25}
E_3	E_{31}	LVS	EQ	VS	ST	VS	LST	E_{32}
	E_{32}	VA	EQ	LST	VS	VS	LWS	E_{33}
	E_{33}	LST	EQ	VS	ST	LST	ST	E_{34}
E_4	E_{41}	ST	LWS	ST	WS	LST	ST	E_{42}
	E_{42}	VS	LST	WS	EQ	VS	EQ	E_{43}

- Step 5: Application of FLPR process to determine the weight of each risk element and their attributes in the hierarchical structure

The weights of the risk elements and attributes of the disruption risk of PRPU operations are estimated using FLPR. Based on the application of FLPR procedure, the subjective response of experts can be transformed into quantitative variables to estimate the weight of risk elements and attributes presented in the hierarchical structure and rank them according to their level of importance.

The feedback from the experts is utilised to construct an incomplete FLPR matrix for a set of *n*-1 preference values as stated in the FLPR process. The incomplete FLPR matrix values are represented in triangular fuzzy importance scale values as detailed in Table 2. The complete FLPR matrix is established using Step 2 of the FLPR procedure.

The whole procedure for establishing the FLPR pairwise comparison matrix and the process of obtaining risk elements weights are illustrated in this study by presenting the evaluation of attributes with respect to a technical risk element. For example, the attributes defined as E_{11}, E_{12}, E_{13} and E_{14}, have only three pairwise comparison judgements ($\tilde{p}_{12,}$ $\tilde{p}_{23}$ $\tilde{p}_{34}$), which means comparisons from E_{11} to E_{12}, from E_{12} to E_{13} and from E_{13} to E_{14} are required to construct the fuzzy linguistic preference relation matrix. The pairwise comparison matrix structure for the attributes relating to the technical risk element is shown in Table 9. Due to the differences in preferences and competencies of the experts, a questionnaire designed based on linguistic assessment variables is used to obtain fuzzy data on pairwise comparisons of the attributes relating to the technical risk element. The fuzzy data obtained from the experts is converted into triangular fuzzy values, which to construct the initial FLPR matrix as shown in Table 10.

The proposition stated in Section 3.4.2, is used to develop the FLPR matrix of the attributes relating to the technical risk elements.

Table 9: Pairwise comparison matrix structure for attributes relating to technical risk element

Attributes	E_{11}	E_{12}	E_{13}	E_{14}
E_{11}	p_{11}	p_{12}	p_{13}	p_{14}
E_{12}	p_{21}	p_{22}	p_{23}	p_{24}
E_{13}	p_{31}	p_{32}	p_{33}	p_{34}
E_{14}	p_{41}	p_{42}	p_{43}	p_{44}

Table 10: Incomplete FLPR pairwise comparison matrix of attributes with respect to technical risk element

Attributes	E_{11}	E_{12}	E_{13}	E_{14}
E_{11}	(0.5, 0.5, 0.5)	(0.39, 0.43, 0.48)	P_{13}	p_{14}
E_{12}	p_{21}	(0.5, 0.5, 0.5)	(0.76, 0.81, 0.85)	p_{24}
E_{13}	p_{31}	p_{32}	(0.5, 0.5, 0.5)	(0.64, 0.69, 0.74)
E_{14}	p_{41}	p_{42}	p_{43}	(0.5, 0.5, 0.5)

Based on the FLPR process, an element p_{ij} can denote the ratio of the preference intensity of an attribute x_i over attribute x_j , which satisfy the condition that p_{ij} = 0.5. Then, this condition implies that no difference exist between attributes x_i and x_j after pairwise comparison. In Table 9, this condition applies to the diagonal elements p_{11}, p_{22}, p_{33} and p_{44} in the matrix structure, which were presented as triangular fuzzy number (0.5, 0.5, 0.5) as shown in Table 10. Also, p_{12}, p_{23} and p_{34} indicate the $n-1$ pairwise comparisons of four attributes with respect to the technical risk element. Hence, the unknown elements in the matrix which are p_{13}, p_{14}, p_{21}, p_{24}, p_{31}, p_{32}, p_{41}, p_{42} and p_{43} are calculated using the FLPR propositions. The complete FLPR matrix for the calculations above is shown in Table 11. The FPLR matrix has certain values, which are not in the interval [0, 1]. Therefore, the FPLR matrix is transformed using the transform function as stated in Section 3.4.1 to preserve the reciprocity and additive consistency of the matrix. Table 12 shows the transformed FLPR matrix. Using the same steps in the FLPR procedure, the FPLR matrices for other attributes with respect to their risk elements and that of the risk element with respect to the goal are estimated and presented in Tables 13, 14, 15, 16, 17, 18 and 19. Furthermore, the average values $(\widetilde{A_\iota})$, the weights$(\widetilde{W})$, and the deffuziffied values of all risk elements and their attributes are calculated and presented in Table 20. Defuzzified values are obtained based on the fuzzy mean and spread method to perform ranking of the risk elements and their attributes according to the level of their importance.

Table 11: Complete FLPR pairwise comparison matrix of attributes with respect to technical risk element

	E_{11}	E_{12}	E_{13}	E_{14}
E_{11}	(0.50,0.50,0.50)	(0.39,0.43,0.48)	(0.65,0.74,0.83)	(0.79,0.98,1.07)
E_{12}	(0.52,0.57,0.61)	(0.50,0.50,0.50)	(0.76,0.81,0.85)	(0.90,1,1.09)
E_{13}	(0.17,0.26,0.35)	(0.15,0.19,0.24)	(0.50,0.50,0.50)	(0.64,0.69,0.74)
E_{14}	(-0.07,0.28,0.46)	(-0.09,0,0.10)	(0.26,0.31,0.36)	(0.50,0.50,0.50)

Table 12: Transform FLPR matrix of technical risk element attributes

	E_{11}	E_{12}	E_{13}	E_{14}
E_{11}	(0.51,0.51,0.51)	(0.41,0.45,0.50)	(0.64,0.72,0.79)	(0.76,0.92,1.0)
E_{12}	(0.53,0.57,0.60)	(0.51,0.51,0.51)	(0.73,0.78,0.82)	(0.85,0.94, 1.0)
E_{13}	(0.22,0.30,0.38)	(0.21,0.24,0.28)	(0.51,0.51,0.51)	(0.63,0.67,0.72)
E_{14}	(0.02,0.09,0.25)	(0,0,0.16)	(0.30,0.34,0.38)	(0.51,0.51,0.51)

Table 13: Incomplete FLPR pairwise comparison matrix of risk elements with respect to goal

	E_1	E_2	E_3	E_4
E_1	(0.5,0.5,0.5)	(0.52,0.57,0.62)	p_{13}	p_{14}
E_2	p_{21}	(0.5,0.5,0.5)	(0.49,0.54,0.61)	p_{24}
E_3	p_{31}	p_{32}	(0.5,0.5,0.5)	(0.56,0.61,0.67)
E_4	p_{41}	p_{42}	p_{43}	(0.5,0.5,0.5)

Table 14: Complete FLPR pairwise comparison matrix of risk elements with respect to goal

	E_1	E_2	E_3	E_4
E_1	(0.50,0.50,0.50)	(0.52,0.57,0.62)	(0.51,0.61,0.73)	(0.57,0.72,0.90)
E_2	(0.38,0.43,0.48)	(0.50,0.50,0.50)	(0.49,0.54,0.61)	(0.55,0.65,0.78)
E_3	(0.27,0.39,0.49)	(0.39,0.46,0.51)	(0.50,0.50,0.50)	(0.56,0.61,0.67)
E_4	(0.10,0.28,0.5)	(0.22,0.35,0.45)	(0.33,0.39,0.44)	(0.50,0.50,0.50)

Table 15: Complete FLRP pairwise comparison matrix attributes with respect to organizational risk element

	E_{21}	E_{22}	E_{23}	E_{24}	E_{25}
E_{21}	(0.50,0.50,0.50)	(0.63,0.68,0.73)	(0.83,0.93,1.03)	(0.74,0.87,1.04)	(0.52,0.81,0.91)
E_{22}	(0.27,0.32,0.37)	(0.50,0.50,0.50)	(0.70,0.75,0.80)	(0.61,0.71,0.81)	(0.39,0.53,0.68)
E_{23}	(-0.03,0.07,0.17)	(0.20,0.25,0.30)	(0.50,0.50,0.50)	(0.41,0.46,0.51)	(0.19,0.28,0.38)
E_{24}	(-0.04,0.13,0.26)	(0.19,0.29,0.39)	(0.49,0.54,0.59)	(0.50,0.50,0.50)	(0.28,0.32,0.37)
E_{25}	(0.09,0.19,0.48)	(0.32,0.47,0.61)	(0.62,0.72,0.81)	(0.63,0.68,0.72)	(0.50,0.50,0.50)

Table 16: Transformed FLRP matrix for organizational risk element attributes

	E_{21}	E_{22}	E_{23}	E_{24}	E_{25}
E_{21}	(0.50,0.50,0.50)	(0.62,0.67,0.71)	(0.81,0.90,0.99)	(0.72,0.84,1.0)	(0.52,0.79,0.88)
E_{22}	(0.29,0.33,0.38)	(0.50,0.50,0.50)	(0.69,0.73,0.78)	(0.60,0.69,0.79)	(0.40,0.54,0.67)
E_{23}	(0.09,0.10,0.19)	(0.22,0.27,0.32)	(0.50,0.50,0.50)	(0.41,0.46,0.51)	(0.21,0.30,0.39)
E_{24}	(0,0.16,0.28)	(0.21,0.31,0.40)	(0.49,0.54,0.58)	(0.50,0.50,0.50)	(0.31,0.33,0.38)
E_{25}	(0.12,0.21,0.48)	(0.33,0.47,0.60)	(0.61,0.70,0.79)	(0.62,0.67,0.70)	(0.50,0.50,0.50)

Table 17: Complete FLPR pairwise comparison matrix of attributes with respect to operational risk element

	E_{31}	E_{32}	E_{33}	E_{34}
E_{31}	(0.50,0.50,0.50)	(0.50,0.55,0.60)	(0.56,0.71,0.76)	(0.69,0.74,0.89)
E_{32}	(0.40,0.45,0.50)	(0.50,0.50,0.50)	(0.56,0.61,0.66)	(0.09,0.19,0.29)
E_{33}	(0.24,0.29,0.44)	(0.34,0.39,0.44)	(0.50,0.50,0.50)	(0.53,0.58,0.63)
E_{34}	(0.11,0.26,0.41)	(0.71,0.81,0.91)	(0.37,0.42,0.47)	(0.50,0.50,0.50)

Table 18: Complete FLPR pairwise comparison matrix of attributes with respect to external risk element

	E_{41}	E_{42}	E_{43}
E_{41}	(0.50,0.50,0.50)	(0.56,0.61,0.66)	(0.61,0.71,0.81)
E_{42}	(0.34,0.39,0.44)	(0.50,0.50,0.50)	(0.55,0.60,0.65)
E_{43}	(0.19,0.29,0.39)	(0.35,0.40,0.45)	(0.50,0.50,0.50)

Table 19: Complete FLPR decision matrix for risk elements and attributes of PRPU operations

	E_1	E_2	E_3	E_4	
E_1	(0.50,0.50,0.50)	(0.52,0.57,0.62)	(0.51,0.61,0.73)	(0.57,0.72,0.9)	
E_2	(0.38,0.43,0.48)	(0.50,0.50,0.50)	(0.49,0.54,0.61)	(0.55,0.65,0.78)	
E_3	(0.27,0.39,0.49)	(0.39,0.46,0.51)	(0.50,0.50,0.50)	(0.56,0.61,0.67)	
E_4	(0.10,0.28,0.5)	(0.22,0.35,0.45)	(0.33,0.39,0.44)	(0.50,0.50,0.50)	
E_1	E_{11}	E_{12}	E_{13}	E_{14}	
E_{11}	(0.51,0.51,0.51)	(0.41,0.45,0.50)	(0.64,0.72,0.79)	(0.76,0.92,1.0)	
E_{12}	(0.53,0.57,0.60)	(0.51,0.51,0.51)	(0.73,0.78,0.82)	(0.85,0.94, 1.0)	
E_{13}	(0.22,0.30,0.38)	(0.21,0.24,0.28)	(0.51,0.51,0.51)	(0.63,0.67,0.72)	
E_{14}	(0.02,0.09,0.25)	(0,0,0.16)	(0.30,0.34,0.38)	(0.51,0.51,0.51)	
E_2	E_{21}	E_{22}	E_{23}	E_{24}	E_{25}
E_{21}	(0.50,0.50,0.50)	(0.62,0.67,0.71)	(0.81,0.90,0.99)	(0.72,0.84,1.0)	(0.52,0.79,0.88)
E_{22}	(0.29,0.33,0.38)	(0.50,0.50,0.50)	(0.69,0.73,0.78)	(0.60,0.69,0.79)	(0.40,0.54,0.67)
E_{23}	(0.09,0.10,0.19)	(0.22,0.27,0.32)	(0.50,0.50,0.50)	(0.41,0.46,0.51)	(0.21,0.30,0.39)
E_{24}	(0,0.16,0.28)	(0.21,0.31,0.40)	(0.49,0.54,0.58)	(0.50,0.50,0.50)	(0.31,0.33,0.38)
E_{25}	(0.12,0.21,0.48)	(0.33,0.47,0.60)	(0.61,0.70,0.79)	(0.62,0.67,0.70)	(0.50,0.50,0.50)
E_3	E_{31}	E_{32}	E_{33}	E_{34}	
E_{31}	(0.50,0.50,0.50)	(0.50,0.55,0.60)	(0.56,0.71,0.76)	(0.69,0.74,0.89)	
E_{32}	(0.40,0.45,0.50)	(0.50,0.50,0.50)	(0.56,0.61,0.66)	(0.09,0.19,0.29)	
E_{33}	(0.24,0.29,0.44)	(0.34,0.39,0.44)	(0.50,0.50,0.50)	(0.53,0.58,0.63)	
E_{34}	(0.11,0.26,0.41)	(0.71,0.81,0.91)	(0.37,0.42,0.47)	(0.50,0.50,0.50)	
E_4	E_{41}	E_{42}	E_{43}		
E_{41}	(0.50,0.50,0.50)	(0.56,0.61,0.66)	(0.61,0.71,0.81)		
E_{42}	(0.34,0.39,0.44)	(0.50,0.50,0.50)	(0.55,0.60,0.65)		
E_{43}	(0.19,0.29,0.39)	(0.35,0.40,0.45)	(0.50,0.50,0.50)		

Table 20: Evaluated weight and ranking of risk elements and attributes of PRPU operations

Risk elements (level 2)	Average	Fuzzy weight	Defuzzified values	Normalized Crisp values	Ranking	
E_1	(0.53,0.60,0.69)	(0.23,0.30,0.40)	0.31	0.30	1	
E_2	(0.48,0.53,0.59)	(0.21,0.27,0.34)	0.27	0.26	2	
E_3	(0.42,0.49,0.52)	(0.19,0.25,0.30)	0.25	0.24	3	
E_4	(0.57,0.72,0.9)	(0.13,0.19,0.27)	0.20	0.20	4	
Attributes (Level 3)					Global weight	Global ranking
E_{11}	(0.58,0.65,0.7)	(0.26,0.32,0.38)	0.28	0.30	0.090	2
E_{12}	(0.65, 0.7, 0.71)	(0.30,0.35,0.39)	0.35	0.36	0.1080	1
E_{13}	(0.39,0.43,0.47)	(0.12,0.19,0.26)	0.19	0.20	0.0600	7
E_{14}	(0.21,0.24,0.33)	(0.10,0.12,0.18)	0.13	0.14	0.0420	14
E_{21}	(0.63,0.93,1.02)	(0.21,0.34,0.47)	0.34	0.33	0.0858	3
E_{22}	(0.50,0.56,0.62)	(0.16,0.21,0.29)	0.22	0.21	0.0546	9
E_{23}	(0.27,0.33,0.38)	(0.09,0.12,0.18)	0.13	0.13	0.0334	16
E_{24}	(0.33,0.37,0.43)	(0.12,0.14,0.20)	0.15	0.14	0.0364	15
E_{25}	(0.44,0.51,0.61)	(0.14,0.19,0.28)	0.20	0.19	0.0494	13
E_{31}	(0.56,0.63,0.69)	(0.25,0.31,0.39)	0.32	0.31	0.0744	5
E_{32}	(0.39,0.44,0.49)	(0.17,0.22,0.27)	0.22	0.22	0.0528	11
E_{33}	(0.40,0.44,0.50)	(0.18,0.22,0.28)	0.23	0.23	0.0522	12
E_{34}	(0.42,0.50,0.57)	(0.19,0.24,0.32)	0.25	0.24	0.0576	8
E_{41}	(0.56,0.61,0.66)	(0.34,0.40,0.48)	0.40	0.40	0.0800	4
E_{42}	(0.46,0.50,0.53)	(0.28,0.33,0.39)	0.33	0.33	0.0660	6
E_{43}	(0.35,0.40,0.45)	(0.21,0.26,0.33)	0.27	0.27	0.0540	10

- Step 5: Ranking decision

The calculation of the weights and ranking of risk elements and their attributes according to their importance level is presented in Table 20. Based on the result obtained, the trend of the ranking in descending order of risk elements in level 2 of the hierarchical model indicates that $E_1 > E_2 > E_3 > E_4$. Also, the trend of ranking of attributes in level 3 based on their global weight indicates that $E_{12} > E_{11} > E_{21} > E_{41} > E_{31} > E_{42} > E_{13} > E_{34} > E_{22} > E_{43} > E_{32} > E_{33} > E_{25} > E_{14} > E_{24} > E_{23}$.

5. Discussion

The ranking order for the level 2 of the hierarchical model, indicates that technical and organizational risk elements are more critical in terms of causing the disruption risk of PRPU operations. Due to the closeness of the ranking value of organizational risk element and operational risk element, we can substantiate that organizational element are risk-influencing elements that has received a lot of attention in safety/risk research. During the past decades, it studies is highly relevant for the operation of safety of socio technical systems (e.g. Rahimi and Rausand (2013); Skogdalen and Vinnem, 2011; Aven *et al.* 2006 Sklet *et al*. 2005; Mearns *et al.* 2001). Various studies across a wide range of socio technical systems have shown a positive correlation between organisational factors and safety performance (Mearns et al., (2003) and Itoh et al., (2004) cited in Reiman and Rollenhagen, 2011). Thus, the outcome of the analyses in this study shows that organizational risk element is relevant in the context specific to organisational perspective on all aspects of safety of a petroleum refinery operation. Furthermore, indications from Bley et al. (1992) cited in Schönbeck et al. (2010), stated that any probabilistic risk model that fails to observe the organisational factors definitely undervalue the overall risk to an undetermined extent. This line of thought clearly substantiate the ranking of organisational element above operational risk element in terms of contributing to disruption risk in a petroleum refinery domain.

The ranking of the attributes in the level 3 of the hierarchical model, indicates that instrument failure, process equipment failure, inappropriate management policy, inappropriate decision making, deviation from operation procedure, inadequate maintenance procedure and natural hazard are considered as the most significant attributes in relation to the risk elements. At present, no benchmark is available, with which the ranking results from this study can be compared. Therefore, the observations from other related works to this research domain, are utilised to substantiate the ranking result in this study. For instance, Moura *et al.,* (2016) analyse multi-attribute accident data set, which include major accidents in the petroleum refining industry. The result of the analysis indicates that equipment failure has a higher rate of recurrence in terms of triggering accidents, when compared to other accident triggering attributes such as inadequate procedure, inadequate communication, maintenance failure and management problem. Saleh *et al.,* (2014), diagnose petroleum refinery accidents triggering attributes such as instrument failure, deviation from operational procedure, inadequate communication and poor/inadequate decisions. However, instrument failure was recognized and analysed in-depth more than the other attributes. This is because of its high probability of developing into an adverse latent condition, which can precipitate the occurrence of a major accident with catastrophic consequence. Kidam and Hurmes, (2013a), conduct a statistical review of major accident cases in the process industry. The analysis identifies that the main contributors to accidents are 78% technical causes, 20% organizational/human causes and 2% external causes. This outcome can be compared to the ranking result of the risk elements in the level 2 of the hierarchical model. Kidam and Hurmes (2013b), concerning the analysis of accident sub contributors indicates that equipment/instrument failure, and deviation from operation procedure, are more critical, when compared to other accident sub-contributors relating to inadequate maintenance, inadequate communication (poor communication) and inadequate decision-making (misjudgment). Zhang and Zheng, (2012) probe the root causes of accidents in the process industries in China. The findings from their work indicate that active equipment/instrument failure is the highest causative factors, when compared to other critical events such as deviation from operation procedure, piping failure, natural hazard and human related causes. Furthermore, Underwood and Waterson (2014) indicated that traditional cause and effect accident models suggest that complex systems accidents are initiated by risky occurrence such as catastrophic equipment failure.

The lowest ranked attributes in relation to the risk elements are poor safety monitoring and audit, utility system failure and lack of safety training/drill. This does not suggest that they are not likely to initiate disruption risk of PRPU operations, but their critical level is relatively low when compared to the other attributes. Based on the rationalisation provided to support the ranking results in this research, it is envisaged that the ranking results are a reliable risk information source to support the risk management process in a petroleum refinery domain.

6. Conclusion

Addressing the issue of disruption risk of PRPU operations is very crucial in order to prevent the risk of catastrophic accidents in a petroleum refinery domain. This study presents a novel methodology using fuzzy linguistic preference relation approach to evaluate the risk elements and attributes which can cause disruption of PRPU operations. The fuzzy linguistic preference relation is utilised to analyse the hierarchical structure of disruption risk of the PRPU operations and to determine the weights of risk elements and attributes, and to obtain the final ranking. In addition, fuzzy linguistic preference relation effectively addresses the uncertainty and the imprecision from subjective judgements of domain experts.

The subjective judgement of multiple experts on four risk elements and sixteen attributes of PRPU disruption risk is represented as fuzzy linguistic assessment variables, which are expressed by triangular fuzzy values to overcome vagueness or ambiguity of the judgements and for easy computation process. Using the FLPR approach provides the most convenient way to reduce the number of pairwise comparisons of risk elements and attributes in a questionnaire sent to domain experts. The questionnaire allows experts to express their response in a consistent manner without prejudice. The result in this study provides valuable reference to duty holders and stakeholders of petroleum refineries to improve their perception about how risk elements and attributes can be critically prioritised in the risk management process. The methodology proves to be a dependable evaluation procedure in terms of its flexibility and ease of application, when compared to other hierarchical modelling methods like fuzzy AHP, which requires more information and consistency checks in the decision making process. Finally, this study has demonstrated that the proposed methodology provides a resourceful, yet flexible approach to solve a risk problem in a practicable manner.

References

ARIA (Analysis, Research and Information on Accidents), (2012). French Ministry of Ecology, sustainable development and energy. Available from: www.aria.developpement-durable.gouv.fr, (last checked 19.03.15).

Baybutt, P., 2003. Inherent Security, Protecting Process Plants Against Threats. *Chemical Engineering Progress, accepted for publication*.

Bea, R.G., 1998. Human and organization factors: engineering operating safety into offshore structures. *Reliability Engineering & System Safety*, *61*(1-2), pp.109-126.

Bley, D., Kaplan, S. and Johnson, D., 1992. The strengths and limitations of PSA: where we stand. *Reliability Engineering & System Safety*, *38*(1-2), pp.3-26.

CBS (2007) BP America Refinery Explosion Texas City, TX, March 23, 2005, Final Report finding, *http://www.csb.gov/*, (last checked 16.10.14).

CSB (2017a) Flash Fire at the Delaware City Refinery Delaware City, DE, November 29, 2015 Final Report finding, *http://www.csb.gov/*,(last checked 08.09.18).

CSB (2017b) ExxonMobil Torrance Refinery Electrostatic Precipitator Explosion Torrance, California, February 18, 2015, Final Report finding, *http://www.csb.gov/*,(last checked 08.09.18).

CSB (2014a) Chevron Richmond Refinery Pipe Rupture and Fire California, CA, August 6, 2012 Final Report Finding, *http://www.csb.gov/*, (last checked 17.11.14).

CSB (2014b) Silver Eagles refinery explosion investigation: Metallurgical Analysis, Utah,TX, November 4, 2009 Final Report Findings, *http://www.csb.gov/*, (last checked 25.09.14).

CSB (2014c) Tesoro Anacortes Refinery Catastrophic Rupture of Heat Exchanger Washington, April 2, 2010 Final Report Finding, *http://www.csb.gov/*, (last checked 15.11.15).

CSB (2008) LPG Fire at Valero Mckee Refinery Sunray, Texas, February 16, 2007 Final Report Finding, *http://www.csb.gov/*, (last checked 10.11.15).

CSB (2001) Tosco Avon Refinery Fire incident Martinez, California, February 23, 1999 Final Report Finding, *http://www.csb.gov/*, (last checked 10.11.15).

Chen, S.J. and Hwang, C.L., 1992. *Fuzzy Multiple Attribute Decision Making-Method and Applications*, Springer, New York, NY, USA.

Chen, Y.H., Wang, T.C. and Wu, C.Y., 2011. Multi-criteria decision making with fuzzy linguistic preference relations. *Applied Mathematical Modelling*, *35*(3), pp.1322-1330.

Chen, Y.H. and Chao, R.J., 2012. Supplier selection using consistent fuzzy preference relations. *Expert Systems with Applications*, *39*(3), pp.3233-3240.

Gordon, R.P., 1998. The contribution of human factors to accidents in the offshore oil industry. *Reliability Engineering & System Safety*, *61*(1-2), pp.95-108.

HSE (2003) Public Report of BP Grangemouth Major Incident Investigation 29 May, 2000, *http://www.hse.gov.uk/comah/accident.htm*, (last checked 10.10.15).

HSE (1997) 'The Explosion and Fire at the Texaco Refinery Milford Haven, 24 July, 1994 *http://www.hse.gov.uk/comah/accident.htm*, (last checked 20.10.15).

HSE (2005) Public Report of the Fire and Explosion at the ConocoPhilips Humber refinery on 16 April 2001, *http://www.hse.gov.uk/comah/accident.htm*, (last checked 03.10.14).

Huang, C.N., Chang, D.S. and Lu, S.T., 2011, July. The analysis of evaluation criteria for of security Firms in Taiwan based on fuzzy linguistic preference relation approach. In *Business Innovation and Technology Management (APBITM), 2011 IEEE International Summer Conference of Asia Pacific* (pp. 250-254). IEEE.

Isimite, J. and Rubini, P., 2016. A dynamic HAZOP case study using the Texas City refinery explosion. *Journal of Loss Prevention in the Process Industries*, *40*, pp.496-501.

Itoh, K., Andersen, H.B. and Seki, M., 2004. Track maintenance train operators' attitudes to job, organisation and management, and their correlation with accident/incident rate. *Cognition, Technology & Work*, *6*(2), pp.63-78.

Khan, F.I. and Amyotte, P.R., 2007. Modeling of BP Texas City refinery incident. *Journal of Loss Prevention in the Process Industries*, *20*(4), pp.387-395.

Kidam, K., Hurme, M. and Hassim, M.H., 2010. Technical analysis of accident in chemical process industry and lessons learnt. *Chemical Engineering Transactions*, *19*, pp.451-456.

Kidam, K. and Hurme, M., 2013. Statistical analysis of contributors to chemical process accidents. *Chemical Engineering & Technology*, *36*(1), pp.167-176.

Kidam, K. and Hurme, M., 2013. Analysis of equipment failures as contributors to chemical process accidents. *Process Safety and Environmental Protection*, *91*(1), pp.61-78.

Knegtering, B. and Pasman, H.J., 2009. Safety of the process industries in the 21st century: A changing need of process safety management for a changing industry. *Journal of Loss Prevention in the Process Industries*, *22*(2), pp.162-168.

Lee, E. S., and Li, R.-J. (1988). Comparison of fuzzy numbers based on the probability measure of fuzzy events. Computers and Mathematics with Applications, 15, 887–896.

Lu, S.T., Yu, S.H., Chang, D.S. and Su, S.C., 2013. Using the fuzzy linguistic preference relation approach for assessing the importance of risk factors in a software development project. *Mathematical Problems in Engineering*, *2013*.

Manca, D. and Brambilla, S., 2012. Dynamic simulation of the BP Texas City refinery accident. *Journal of Loss Prevention in the Process Industries*, *25*(6), pp.950-957.

Markowski, A.S., Mannan, M.S., Kotynia, A. and Siuta, D., 2010. Uncertainty aspects in process safety analysis. *Journal of Loss Prevention in the Process Industries*, *23*(3), pp.446-454.

Mearns, K., Whitaker, S.M. and Flin, R., 2003. Safety climate, safety management practice and safety performance in offshore environments. *Safety science*, *41*(8), pp.641-680.

Mohaghegh, Z., Kazemi, R. and Mosleh, A., 2009. Incorporating organizational factors into Probabilistic Risk Assessment (PRA) of complex socio-technical systems: A hybrid technique formalization. *Reliability Engineering & System Safety*, *94*(5), pp.1000-1018.

Moura, R., Beer, M., Patelli, E., Lewis, J. and Knoll, F., 2016. Learning from major accidents to improve system design. *Safety science*, *84*, pp.37-45.

Nolan, D.P., 2014. Handbook of fire and explosion protection engineering principles: for oil, gas, chemical and related facilities. William Andrew.

Øien, K., Utne, I.B., Tinmannsvik, R.K. and Massaiu, S., 2011. Building safety indicators: Part 2–application, practices and results. *Safety science*, *49*(2), pp.162-171.

Pasman, H.J., Knegtering, B. and Rogers, W.J., 2013. A holistic approach to control process safety risks: Possible ways forward. *Reliability Engineering & System Safety*, *117*, pp.21-29.

Qi, R., Prem, K.P., Ng, D., Rana, M.A., Yun, G. and Mannan, M.S., 2012. Challenges and needs for process safety in the new millennium. *Process safety and environmental protection*, *90*(2), pp.91-100.

Reiman, T. and Rollenhagen, C., 2011. Human and organizational biases affecting the management of safety. *Reliability Engineering & System Safety*, *96*(10), pp.1263-1274.

Reniers, G. and Amyotte, P., 2012. Prevention in the chemical and process industries: Future directions. *Journal of Loss Prevention in the Process Industries*, *25*(1), pp.227-231.

Rodríguez, J.M., Payne, S.C., Bergman, M.E. and Beus, J.M., 2011. The impact of the BP baker report. *Journal of safety research*, *42*(3), pp.215-222.

Saleh, J.H., Haga, R.A., Favarò, F.M. and Bakolas, E., 2014. Texas City refinery accident: Case study in breakdown of defense-in-depth and violation of the safety–diagnosability principle in design. *Engineering Failure Analysis*, *36*, pp.121-133.

Shin, I. J. (2013). The effective control of major industrial accidents by the Major Industrial Accident Prevention Centers (MAPC) through the Process Safety Management (PSM) grading system in Korea. *Journal of Loss Prevention in the Process Industries*, 26(4), 803-814.

Shin, I. J. (2014). Loss prevention at the startup stage in process safety management: From distributed cognition perspective with an accident case study. *Journal of Loss Prevention in the Process Industries,* 27*,* 99-113.

Schönbeck, M., Rausand, M. and Rouvroye, J., 2010. Human and organisational factors in the operational phase of safety instrumented systems: A new approach. *Safety Science*, *48*(3), pp.310-318.

Thomson, J., 2013. Refineries and Associated Plant: Three Accident Case Studies. *Safety In Engineering Ltd, New York, New York*.

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.

Underwood, P. and Waterson, P., 2014. Systems thinking, the Swiss Cheese Model and accident analysis: a comparative systemic analysis of the Grayrigg train derailment using the ATSB, AcciMap and STAMP models. *Accident Analysis & Prevention*, *68*, pp.75-94.

Wang, T.C. and Chen, Y.H., (2005). A new method on decision-making using fuzzy linguistic assessment variables and fuzzy preference relations. In Paper presented at the 9th world multi-conference on systemic, cybernetics and informatics (WMSCI 2005), Orlando, Florida, USA, 2005.

Wang, T.C. and Chang, T.H., 2007. Application of consistent fuzzy preference relations in predicting the success of knowledge management implementation. *European Journal of Operational Research*, *182*(3), pp.1313-1329.

Wang, T.C. and Chen, Y.H., 2008. Applying fuzzy linguistic preference relations to the improvement of consistency of fuzzy AHP. *Information Sciences*, *178*(19), pp.3755-3765.

Wang, T.C. and Lin, Y.L., 2009. Applying the consistent fuzzy preference relations to select merger strategy for commercial banks in new financial environments. *Expert Systems with Applications*, *36*(3), pp.7019-7026.

Wang, T.C., and Chen, Y.H. (2010). Incomplete fuzzy linguistic preference relations under uncertain environment. Information Fusion, 11, 201–207.

Wang, T.C. and Chen, Y.H., 2011. Fuzzy multi-criteria selection among transportation companies with fuzzy linguistic preference relations. *Expert Systems with Applications*, *38*(9), pp.11884-11890.

Wood, M.H., Arellano, A.V. and Van Wijk, L., 2013. Corrosion Related Accidents in Petroleum Refineries. *European Commission Joint Research Centre, report no. EUR, 26331*.

Wu, P.P.Y., Fookes, C., Pitchforth, J. and Mengersen, K., 2015. A framework for model integration and holistic modelling of socio-technical systems. *Decision Support Systems*, *71*, pp.14-27.

Zhang, H.D. and Zheng, X.P., 2012. Characteristics of hazardous chemical accidents in China: A statistical investigation. *Journal of Loss Prevention in the Process Industries*, *25*(4), pp.686-693.